2019

Long-Term Urban Forest Cover Change Detection with Object Based Image Analysis and Random Point Based Assessment

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By

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A Thesis Submitted in Partial Fulfillment of the

Requirements for the Degree of

Master of Science

In

Geography

Minnesota State University, Mankato

Mankato, Minnesota

December 2019

6th December 2019

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This thesis has been examined and approved by the following members of the student's committee.

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Acknowledgments

I would like to thank the members of my student committee: my advisor, Professor Fei Yuan for her patience, guidance and ability to impart her vast knowledge, Professor Woo Jang for helping to clarify that a Geography Master's degree at Minnesota State University was what I wanted to do, and Professor Cindy Miller, who was instrumental in shaping the topic of my thesis. I would also like to thank the geography department faculty, every class I took was of immense benefit and value, and the staff who made my experience at Minnesota State University that much better. I am grateful to have received the 2019-2020 James F. Goff Graduate Research Award and the 2019-2020 Dr. Mary Dooley Scholarship Award. Finally, I would like to thank my partner Professor Thia Cooper, without whom the Master's thesis would not have been possible.

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Minnesota State University, Mankato

December 2019

Abstract

The urban forest provides various ecosystem services. Urban tree canopy cover measurement is the most basic quantification of ecosystem services. There have been few studies focused on long-term high-resolution urban forest change analysis. Further, few if any of these studies have compared object based image analysis (OBIA) and random point based assessment for determination of urban forest cover. The research objective is to define the urban forest canopy area, location, and height within the City of St Peter, MN boundary between 1938 and 2019 using both the OBIA and random point based methods with high spatial-resolution aerial photographic images and Light Detection and Ranging (LiDAR) data. One facet of this project is to examine the impact of natural disasters, such as the 1998 tornado, and tree diseases on the urban canopy cover area. LiDAR data was used to determine the height and canopy cover density of the urban forest canopy. The results were used to compare and contrast the methods, with verification via ground truthing. Results show that both methods gave comparable accurate results. The total canopy cover area remained consistent until 1995, then increased post-tornado. The location of canopy cover areas has changed throughout St Peter over time due to the

tornado, the increase in size of the City of St Peter, and land use change within the City of St Peter. The canopy change due to diseases was not detectable.

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1. Introduction

1.1 Project Overview

Urban tree canopy cover measurement is the most basic quantification of potential ecosystem services provided by the urban forest, such as regulating (air purification, water filtration). Historically, there have been relatively few studies that have been focused on long-term high-resolution urban forest change analysis. Further, few if any of these studies have compared and contrasted object based image analysis (OBIA) and random point based assessment for determination of urban forest cover utilizing freely available remote sensing data.

The City of St Peter is situated within the Minnesota valley with the Minnesota River on the east boundary and a bluff to the west, approximately 60 miles south of the Twin Cities (Figure 1) in south central Minnesota. The total area covered by the City is 5.7 square miles and the population is approximately 11,400 (City of Saint Peter 2017). The majority of the street tree population consists of ash (*Fraxinus* spp.) and maple (Acer spp.), with other species present such as basswood (Tilia spp) and hackberry (Celtis spp.) (City of Saint Peter 2018). The objective of the research is to define the urban forest canopy area, location, density, and height within the City of St Peter boundary between 1938 and 2019 utilizing high spatial-resolution aerial photographic images as well as Light Detection and Ranging data (LiDAR). One facet of this project is to examine the impact of natural disasters, such as the 1998 tornado, and tree diseases, e.g., Dutch Elm Disease (DED) and Butternut Canker, on the urban canopy cover area.

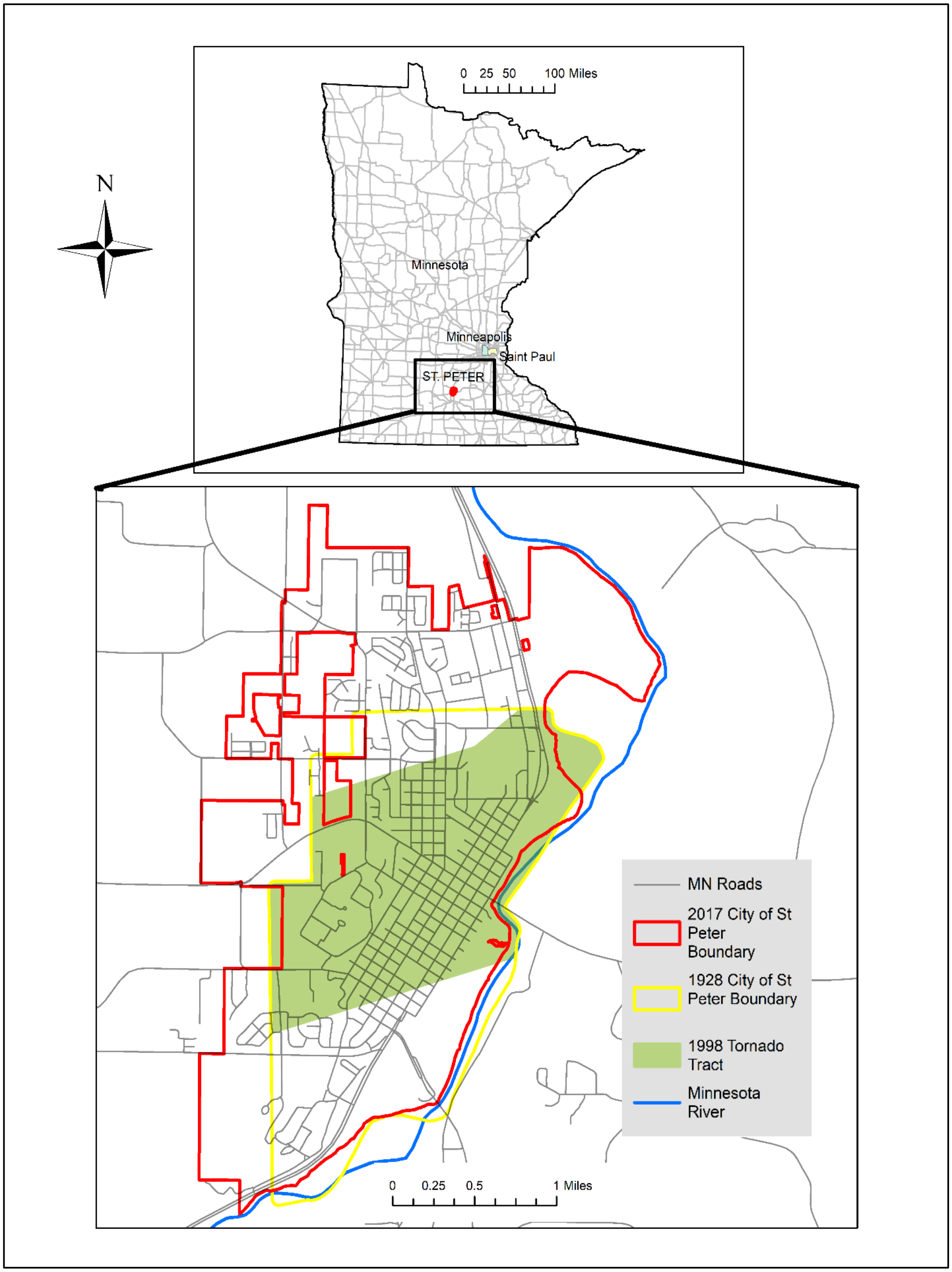

Figure 1. Location of research area

1.2 The Urban Forest

The term Urban Forest has different meanings dependent on your native language and the country that you live in (Konijnendijk et al. 2005; Konijnendijk et al. 2006). The research into the origins of the term have focused primarily on the United States of America (USA) and Europe (Konijnendijk et al. 2006; Gerhold 2007). Homo sapiens have been living with and utilizing trees since before the written word; the earliest recorded use of the word “tree” was in 5800 B.C. (Campana 1999). Arboricultural praxis, generally defined as the traditions, customs, and procedures used to care for perennial woody plants (trees and vines) in the landscape (Harris 1983; Campana 1999; Lilly 2010), has also been utilized in conjunction with individual tree use for millennia (Campana 1999).

In Europe, the concept of trees within an urban environment has been acknowledged since the 1600s (Konijnendijk et al. 2006; Gerhold 2007) and in the USA since the 1900s (Ricard 2005). Prof. Erik Jorgensen, a Professor from the University of Toronto, first applied the term urban forest in 1965 (Konijnendijk et al. 2006; Gerhold 2007; Jonnes 2016).

There are a variety of definitions for the term urban forest (Konijnendijk et al. 2006; Gerhold 2007); the most applicable definition is from the Society of American Foresters as quoted in Konijnendijk et al. (2006), “the art, science and technology of managing trees and forest resources in and around urban community ecosystems for the physiological, sociological, economic and aesthetic benefits trees provide society.” Hence, the urban forest provides a variety of benefits to urban communities; these potential benefits and costs are collectively called ecosystem services (Nowak and Dwyer 2007; Roy, Byrne, and Pickering 2012; Delshammar, Östberg, and Öxell 2015).

1.3 Arbor Day and Tree City USA

The urban forest as a concept and reality has been with us for some historical time. In the next section, I will be discussing the importance of the urban forest regarding its benefits to the urban landscape (ecosystem services). Before we move on, there are two important events worth mentioning in the formation, amalgamation, and consolidation of the concept of the urban forest within the USA.

The first is Arbor Day. The concept of Arbor Day was presented to the Nebraska State Board as a resolution in 1872 by J. Sterling Morton. It was initially only celebrated in Nebraska, then within ten years in Kansas and Minnesota, but now 147 years later is celebrated in all 50 states, some states even observing a week or a month of tree planting celebrations (Miller 1988; Campana 1999; Jonnes 2016). Morton, quoted in Miller (1988), stated that it is a day "especially set apart and consecrated to tree planting in the State of Nebraska and the State Board of Agriculture hereby name it Arbor Day."

The second event is the creation of Tree City USA. In 1972 the Arbor Day Foundation (ADF) was created with the incorporation of Arbor Day; subsequently it became known as the National Arbor Day Foundation (Campana 1999; Jonnes 2016). One of the remits for the foundation was to create programs to highlight arboriculture; Tree City USA was one such program, created in 1976 by John Rosenow (Rosenow and Yager 2007; Jonnes 2016), initiated due to the concern regarding the lack of management of trees within cities (Campana 1999). The program was backed by the U.S. Forest

Service, National Association of State Foresters, the U.S. Conference of Mayors, and the National League of Cities (Campana 1999; Jonnes 2016). The concept was simple: to become a Tree City certain criteria had to be met, including the city having a tree board or city forester, spending a minimum of $2 per citizen on urban forestry projects, and having an ordinance specifically related to tree care.

The yearly Arbor Day planting celebration and Tree City status has played a pivotal role in keeping trees within the public perception and creating an education platform for helping to understand, plant, and grow the urban forest we know today (Miller 1988; Campana 1999; Rosenow and Yager 2007). It should be noted, however, that there are differences between Tree City USA participant cites as well as between non-participants. Even though it was a small sample size, Galvin and Bleil (2004) in Maryland surmised the bigger the populace total, the more likely to participate. Tree City USA participants had a larger quantity of canopy cover per population than non-participating cites but non-participating cities had a larger quantity of canopy cover for a given area, suggesting that Tree City USA in Maryland is achieving its goal of promoting urban forestry in areas with high populations and small urban forests and populations of trees (Galvin and Bleil 2004). A 2016 paper researching the national participation assessment of Tree City USA, Berland, Herrmann, and Hopton (2016) concurred that a higher population meant more likely participation. However, for populations of minorities or the uneducated there is not equal distribution of Tree City USA participation (Berland, Herrmann, and Hopton 2016).

1.4 Ecosystem Services

Ecosystem services are benefits that the urban forest provides to humans and have a direct relationship to humans in the urban setting (Table 1); conversely, the urban forest is valued through ecosystem services. Ecosystem services can be broken down into four categories: supporting (biodiversity, habitat, and soil ecosystems), regulating (air quality, climate regulation), cultural (health and physical activity), and provisioning (fresh water, material, and energy) (Grant 2015).

Dr. Kathleen Wolf, a research social scientist at the University of Washington, WA, in her presentation at the Minnesota Shade Tree Short Course (Bethel College, MN, 2019) gave examples of cultural ecosystem services that have spanned nearly 40 years of research. She recommended attendees to go to the University of Washington website, Green Cities: Good Health (University of Washington 2018), where research topics are divided into themes, including Mental Health & Function, Crime & Public Safety, and Livable Cities. These cultural ecosystem service topics along with the other types of ecosystem services will be discussed at greater length in the literature review.

Table 1. Ecological service benefits associated with trees (Grant 2015)

Benefits	Description
Saving Energy	Trees can modify climate and conserve building energy by shading (reduces energy absorption), evapotranspiration (the process uses solar energy which subsequently cools the air), and by reducing wind speed (mitigates infiltration and heat loss) (Akbari et al., 2001)
Reducing CO_2	Trees directly sequester CO_2 in stems and leaves while they grow. Trees near buildings reduce heating and cooling costs subsequently lowering emissions associated with power production (McHale et al., 2007)
Improving air quality	Trees absorb gaseous pollutants (e.g., O_3, NO_2 and SO_2) through leaf surfaces. Trees intercept PM_{10} (e.g., dust ash, pollen, smoke) and release oxygen through photosynthesis. Transpiration of water and shading of surfaces subsequently lowers air temperatures thereby reducing O_3 levels. Trees reduce energy use which reduces emissions of pollutants from power plants including NO_2, SO_2, PM_{10} and BVOCs. Trees reduce evaporative hydrocarbon emissions and O_3 formation by shading paved surfaces and parked cars (Nowak et al., 2006)
Reducing storm water runoff	Leaves and branch surfaces intercept and store rainfall thereby reducing runoff volumes and delaying peak flows. Roots increase the rate at which rainfall infiltrates soil as well as the soil's storage capacity. Trees reduce soil erosion by reducing the impact of the raindrops on barren surfaces. Transpiration through leaves reduces soil moisture content thereby increasing the soil's capacity to store rainfall (McPherson et al., 2007)
Aesthetics and other benefits	Urban trees improve the aesthetic aspects of urban environments (Smardon, 1988) promote physical activity (Kaczynski and Henderson, 2007) and nearness to natural settings can reduce crime rates (Kuo and Sullivan, 2001b) and aggressive behaviors (Kuo and Sullivan, 2001a}

1.5 Urban Forest Assessment

Ecosystems services are affected by the size, composition, and health of the urban forest. Assessment of the urban forest is therefore crucial to determine the above factors. The most accurate way to collect tree attribute data is by trained personnel going to individual trees within an urban forest. However, tree inventories can be resource intensive, being both time and financially consuming. In addition, it is often not physically possible or legal to get access to every tree within an urban environment.

The use of remote sensing (remote assessment) such as satellite images, photographic images, LiDAR, etc. (Lillesand, Kiefer, and Chipman 2015), to assess the urban forest offers the potential to collect data for the majority of trees within an urban forest in a timely and cost effective manner. Remote sensing can show how the urban forest has changed over time or in response to natural disasters, e.g., species structure, canopy cover, canopy height, etc. (Nowak et al. 1996). One important aspect when looking at the urban forest is to view and review its historical context. It is important to know the size and location of the urban forest in the past and to see if it has increased or decreased. It can also show how events such as the 1998 tornado in the City of St Peter, and past tree diseases, e.g., DED and Butternut Canker, have affected the urban forest.

For the City of St Peter, this information will prove indispensable for the management of locations for tree species to be planted, what species to plant, and policies to maintain the health of the urban forest. The evaluation of ecosystem services will help define the benefits and costs of the urban forest to the City administration and City council. Evaluation of the urban forest with knowledge of past urban forest management practices can determine how future practices are performed and changed, e.g., how best to manage the current threat to the urban forest from the Emerald Ash Borer based on knowledge of the effect of DED. Furthermore, the methodology used in this study including the use of freely available data will be beneficial to other urban foresters and communities as they determine the value of the urban ecosystem services and impacts of natural disasters.

2. Literature Review

2.1 Introduction

This literature review considers the literature present on the urban forest, ecosystem services, remote sensing, Global Positioning Systems (GPS), Geographical Information Systems (GIS), Land Use/Land Class extraction (LULC), and the relationship between the urban forest and natural disasters. The review will create insight into and define the intersection of the topics. Ultimately, this will allow the comprehension of how the urban forest interacts with and benefits urban communities via ecosystem services, and how to determine and examine tree attributes and variables that combine to become the urban forest. In addition, natural disasters like the tornado that affected the City of St Peter, Minnesota (MN), USA in 1998 have a profound effect on the urban forest age, species, and canopy structure and size, etc.; utilizing remote sensing will help to quantify changes over time.

The review is based on over 110 books, thesis, and articles published between 1971 and 2019 (Table 2 & 3). The papers cited have a global geographic range encompassing Europe, East Asia, China, USA, and Canada. This review defines the urban forest and ecosystem services, examines ground and remote assessment of the urban forest, extraction of variables, and briefly describes the literature found on natural disasters, e.g., tornadoes and tree diseases within the urban forest.

Table 2. Literature review summary table, the urban forest, urban forest ecosystem services, urban forest assessment

Literature Review Chapter Section #	**Topic**	**Citations**
2.2	**The Urban Forest**	
2.2.1	**History of Urban Forestry**	Konijnendijk et al. 2005; Ricard 2005; Konijnedijk et al. 2006; Gerhold 2007; Jonnes 2016
2.2.2	**Definition of the Urban Forest & Canopy Cover**	Miller 1988; Jennings, Brown, and Sheil 1999; Rautiainen, Stenberg, and Nilson 2005; Konijnedijk et al. 2006; Gerhold 2007; Nowak et al. 2013; Korhonen and Morsdorf 2014; Nowak et al. 2015; Berland, Herrmann, and Hopton 2016; Knight, Host, and Rampi 2016; Melaas et al. 2016; Plowright et al. 2016; Cowett and Bassuk 2017
2.3	**Urban Forest Ecosystem Services**	Nowak and Dwyer 2007; Roy, Byrne, and Pickering 2012; Delshammar, Östberg, and Öxell 2015; Grant 2015
2.3.1	**Ecosystem Benefits**	Harris 1983; Ulrich 1984; Miller 1988; Nowak and Dwyer 2007; Jiang, Chang, and Sullivan 2014; Jiang et al. 2014; Grant 2015; Edmondson et al. 2016; Melaas et al. 2016; Dadea et al. 2017; Kondo et al. 2017
2.3.2	**Ecosystem Costs or Disservices**	Nowak and Dwyer 2007; Roy, Byrne, and Pickering 2012; Delshammar, Östberg, and Öxell 2015; Vogt, Hauer, and Fischer 2015; Conway and Yip 2016;
2.3.3	**Cost-Benefit Analysis**	Nowak and Dwyer 2007; Nowak et al. 2013; Grant 2015; Bodnaruk et al. 2017; USDA 2018a, b
2.4	**Urban Forest Assessment**	Wood 1999; Wolowicz and Gera 2007; Nowak 2008
2.4.1	**Ground Assessment**	Wolowicz and Gera 2007; Ward and Johnson 2007; Nowak 2008; Mekik and Arslanoglu 2009; Ahmadzadeh et al. 2015; Hawthorne et al. 2015; Nowak et al. 2015; Olokeogun, Akintola, and Abodunrin 2016
2.4.2	**Remote Data Collection**	Lillesand, Kiefer, and Chipman 2015
2.4.2.1	**Photographic Images and Optical Satellites**	Nowak et al. 1996; Wulder 1998; Voss and Sugumaran 2008; Morgan and Gergel 2010; Morgan, Gergel, and Coops 2010; Nowak and Greenfield 2010; Moskal, Styers, and Halabisky 2011; Lillesand, Kiefer, and Chipman 2015; Knight, Host, and Rampi 2016; Thenkabail, Lyon and Huete 2011; Ucar et al. 2016; Chen et al. 2017; Ma, Su, and Guo 2017;
2.4.2.2	**Light Detecting and Ranging (LiDAR)**	Lefsky et al. 2002; Lim et al. 2003; Chen et al. 2006; Omasa et al. 2007; Secord and Zakhor 2007; Voss and Sugumaran 2008; Zhang and Qiu 2011; Li et al. 2012; Yao, Krzystek, and Heurich 2012; Shrestha and Wynne 2012; Tang, Dong, and Buckles 2013; Roberts 2014; Zhang, Zhou, and Qiu 2015; Hovi et al. 2016; Knight, Host, and Rampi 2016; Parmehr, Amati, and Fraser 2016; Plowright et al. 2016; Song et al. 2016; Sumnall, Hill, and Hinsley 2016; Zhen, Quackenbush, and Zhang 2016; Birdal, Avdan, and Türk 2017; Lindberg and Holmgren 2017

Table 3. Literature review summary, urban forest analysis, uncertainty, error assessment and validation of land cover/land use classes, natural disasters and the urban forest

Literature Review Chapter Section #	**Topic**	**Citations**
2.5	**Urban Forest Analysis**	
2.5.1	**Object Based Image Analysis**	Wulder 1998; Yu et al. 2006; Walker and Briggs 2007; Hay et al. 2008; Zhou and Troy 2008; Blaschke 2010; Morgan, Gergel, and Coops 2010; Myint et al. 2011; Moskal, Styers, and Halabisky 2011; Hussain et al. 2013; Meneguzzo, Liknes, and Nelson 2013; Morgan and Gergel 2013; Li and Shao 2014; Wang and Weng 2014; Lillesand, Kiefer, and Chipman 2015; Tewkesbury et al. 2015; Pu, Landry, and Yu 2018;
2.5.2	**i-Tree Software**	Walton, Nowak, and Greenfield 2008; Nowak et al. 2013; Grant 2015; Strunk et al. 2016; Bodnaruk et al. 2017
2.6	**Uncertainty, Error Assessment and Validation of Land Cover/Land Use Classes**	Hoffman and Markman 2001; Walton, Nowak, and Greenfield 2008; Richardson and Moskal 2014; Wang and Weng 2014; Lillesand, Kiefer, and Chipman 2015; Chen et al. 2017; Congalton and Green 2019
2.7	**Natural Disaster and the Urban Forest**	
2.7.1	**Tornados**	Fujita 1971; Holland, Riordan, and Franklin 2006; Beck and Dotzek 2010; Bloniarz and Brooks 2011; Karstens et al. 2013; Micozzi, and Magsig 2002; Burgess et al. 2014; Gokaraju et al. 2015; Kingfield and de Beurs 2017
2.7.2	**Tree Diseases**	Townsend, Bentz, and Douglass 2005
2.7.2.1	**Emerald Ash Borer**	BenDor and Metcalf 2006; Muirhead et al. 2006; Mercader et al. 2009; Prasad et al. 2010; Siegert et al. 2011; McCullough and Mercader 2012; Anderson and Dragićević 2015; Davidson and Rieske 2016; Fahrner et al. 2017; Hauer and Peterson 2017; Spei and Kashian 2017; Fahrner et al. 2017; Cuddington et al. 2018
2.7.2.2	**Dutch Elm Disease**	Strobel and Lanier 1981; Brasier and Buck 2001; Giblin and Gillman 2009
2.7.2.3	**Butternut Canker**	Ostry and Woeste 2004; Broders et al. 2015; Morin et al. 2018

2.2 The Urban Forest

2.2.1 History of Urban Forestry

The concept of the urban forest, if not the term, has been with us since at least the 1600s in Europe (Konijnendijk et al. 2006; Gerhold 2007). In the USA during the early 1900s, the precursor to the legal and conceptual definition of urban forestry occurred in New England. This was due to the threat of damage to trees within the urban environment due to urbanization and industrialization, e.g., road expansion, trenching, etc. (Ricard 2005). The expression urban forestry is first known to have been used by Prof. Erik Jorgensen at University of Toronto in 1965, who needed a title for a student's graduate thesis (Konijnendijk et al. 2006; Gerhold 2007; Jonnes 2016). However, Ricard (2005) stated that it may have been conceivably defined first by George R. Cook who was the Superintendent of Parks in Cambridge Massachusetts during the late 1800s. It subsequently became a popular term to use in the USA during the 1970s and reached the shores of Europe in the 1980s (Konijnendijk et al. 2005).

2.2.2 Definition of the Urban Forest & Canopy Cover

Prof. Erik Jorgensen wrote in 1970 the following urban forest description, quoted in (Konijnendijk et al. 2006; Gerhold 2007):

> Urban forestry is a specialized branch of forestry and has as its objectives the cultivation and management of trees for their present and potential contribution to the physiological, sociological and economic well being of urban society. These contributions include the overall ameliorating effect

of trees on their environment, as well as their recreational and general amenity value.

Some other definitions of urban forestry were described in Konijnendijk et al. (2006) for the federal Cooperative Forestry Act of 1978, "… the planning, establishment, protection and management of trees and associated plants, individually, in small groups, or under forest conditions within cities, their suburbs and towns." One final quote of interest is from the Society of American Foresters in the 1970s as quoted in Konijnendijk et al. (2006), "the art, science and technology of managing trees and forest resources in and around urban community ecosystems for the physiological, sociological, economic and aesthetic benefits tree provide society."

Urban forestry can be divided into sub-disciplines dependent on your specialist interest, e.g., municipal forestry manages public land, utility forestry manages trees near powerlines, etc. In addition, another aspect of urban forestry is silviculture. Urban silviculture is the practice of growing a sustainable urban forest. This practice usually refers to stands or grouping of trees within a naturalized or seeded area, e.g., riparian area, but there is a cross over with respect to individual trees and arboriculture (Miller 1988).

What is the definition of "urban" and "forest" within the term urban forest? The definition of urban changes through time, dependent on the concentration of humans within a given area (Nowak et al. 2001) and human perception and definition of what is rural and urban (Miller 1988; Konijnendijk et al. 2006). It is also important to acknowledge that there is not a defined line between urban and rural, particularly as you pass temporally through landscape change in part due to the changing structure of communities (Miller 1988; Konijnendijk et al. 2006). The most frequently used solution to the question of what is urban for scholars and urban foresters is to define urban within the context of their work. When assessing urban forests in the conterminous USA, Nowak et al. (1996) used three types of census data to define the urban setting; at the other end of the spectrum, artificial boundaries can be used to define urban area, e.g., municipal city boundary.

How is the forest in the term urban forest defined? Again, in a similar fashion to the term urban, forest has no clear definitions. In its most expansive form it is any type of vegetation within the defined urban environment, sometimes referred to as urban greenspace (Roy, Byrne, and Pickering 2012; Edmondson et al. 2016). Within this wide-ranging definition, there is often a focus on all trees within the defined urban environment, excluding shrubs or vines (Nowak et al. 2013; Knight, Host, and Rampi 2016; Melaas et al. 2016; Plowright et al. 2016). A subset focuses only on municipal street trees due to their public ownership (Nowak et al. 2015; Berland, Herrmann, and Hopton 2016; Cowett and Bassuk 2017).

Canopy cover is defined in various ways; the most common definition comes from Jennings, Brown, and Sheil (1999): “Canopy cover refers to the proportion of the forest floor covered by the vertical projection of the tree crowns.” Further, Rautiainen, Stenberg, and Nilson (2005) refine the definition: “effective canopy cover takes into account both gaps between crowns and within crowns.” Korhonen and Morsdorf (2014) also use this definition, as does this research project.

2.3 Urban Forest Ecosystem Services

The urban forest is valued through a process known as ecosystem services. Ecosystem services offer benefits as well as a cost/potential disservice to the population (Nowak and Dwyer 2007; Roy, Byrne, and Pickering 2012; Delshammar, Östberg, and Öxell 2015). To determine the ecosystem services, the urban forest needs to be assessed to quantify the health, species diversity, and the size and location of the urban forest. Ecosystem services are divided into four categories: one, regulating, e.g., air purification, water filtration; two, supporting, e.g., ecological services, soil management; three, cultural, e.g., physical, recreational, and mental health benefits; and four, provisioning, e.g., food, resources, and fuel (Delshammar, Östberg, and Öxell 2015; Grant 2015).

2.3.1 Ecosystem Benefits

All four of the ecosystem services will be discussed briefly within this literature review. Provisioning, however, has not been cited in the papers but from the author's personal experience employed as an urban forester, timber utilization in its many forms is a very important generation of revenue and a valuable resource for a community. Examples of wood use within the community are as an energy resource, e.g., wood used in fires either as household heat or mulched and sold to wood burning power plants; timber is also utilized by sawmills both commercial and private to make furniture, e.g., black walnut (*Juglans nigra*).

Some examples of the importance of regulating ecosystem services, discussed in the literature, are mitigating the urban heat island effect and air pollution. The urban heat island effect is the temperature increase linked to the urban environment as contrasted to the surrounding land. The increase in heat is related to impermeable surfaces that decrease evaporation, absorb shortwave radiation, and decrease longwave energy loss back into the atmosphere. The raised temperature elevations have impacts on human health and ecosystems (Edmondson et al. 2016; Melaas et al. 2016). Edmondson et al. (2016) and Melaas et al. (2016) both inferred the urban forest moderates and reduces the heat island effect.

The improvement in air quality via air purification takes place in trees in multiple ways; one example is the interception of particulate matter (PM_{10}), e.g., dust, pollen, ash, etc. This is accomplished in three ways: one, gravity: reduction in air movement causes heavy particles to fall to surface; two, absorption: trees, particularly conifers, trap particulate matter within their leaves/needles; and three, precipitation: removal of PM_{10} from surface of trees during precipitation events. The second example is the removal of gases potentially detrimental to human health, e.g., O_3, $SO_{2,}$ and NO_2 through absorption into plant tissue (Harris 1983; Miller 1988; Grant 2015; Dadea et al. 2017).

Cultural ecosystem services have been discussed at least since Ulrich (1984) in his seminal paper “View through a window may influence recovery from surgery”. One aspect of cultural ecosystem services discussed within the literature research was how the urban forest influences crime rates and human stress levels and well-being (Nowak and Dwyer 2007; Jiang, Chang, and Sullivan 2014; Jiang et al. 2014; Kondo et al. 2017). Kondo et al. (2017) asked in what way the Emerald Ash Borer (EAB) has influenced urban forest deforestation and if this deforestation has had any effect on the crime rate in Cincinnati. The results of the paper conclude that a decrease in the urban forest due to

EAB can be associated with an upsurge in rates of crime in Cincinnati (Kondo et al. 2017).

Jiang et al. (2014) determined in their paper "A dose-response curve describing the relationship between urban tree cover density and self-reported stress recovery" that stress recovery can be "significantly" greater with a high density of trees. Further, Nowak and Dwyer (2007) stated that "reduced stress and improved physical health for urban residents have been associated with the presence of urban trees and forests in a number of environments." (36). An interesting aside regarding stress and gender: in their paper, Jiang, Chang, and Sullivan (2014), determined that for women there was no relationship between changes in the density of the tree canopy and reduction of stress levels; however for men, for maximum stress level reduction, tree density ideally was between 1.7% and 24% (Jiang, Chang, and Sullivan 2014).

Finally, the urban forest can be viewed as a supporting asset that contributes to urban wildlife biodiversity and in turn a decline in biodiversity can be an indicator of decline in the health of the urban ecosystem (Nowak and Dwyer 2007). Urban wildlife contributes to the comfort and welfare of the populace (Miller 1988) but can also be reservoirs for wildlife species that are at risk (Nowak and Dwyer 2007).

2.3.2 Ecosystem Costs or Disservices

In the previous section some ecosystem benefits of the urban forest were analyzed. More emphasis on research for benefits has been done than on costs/disservices of the urban forest as highlighted in Roy, Byrne, and Pickering (2012), Conway and Yip (2016), and discussed in Vogt, Hauer, and Fischer (2015) where only 18 of the 115

(15.6%) papers reviewed in Roy, Byrne, and Pickering (2012) contained reference to the issue of cost/disservice. Some urban forest costs/disservices include:

A. Tree maintenance, e.g., tree removal, planting, pruning, watering, and management of tree risks (Nowak and Dwyer 2007; Roy, Byrne, and Pickering 2012)

B. Reduction in light, e.g., reduction in street lighting intensity due to canopy cover (Roy, Byrne, and Pickering 2012)

C. Human health, e.g., pollen and Volatile Organic Compounds (VOC) production by trees (Nowak and Dwyer 2007)

D. Damage to infrastructure, e.g., sidewalk damage due to roots (Roy, Byrne, and Pickering 2012)

In addition, other less easily quantifiable costs/disservices are fears or risk (either real or perceived), e.g., fear of a crime happening in an area heavily populated by trees (Delshammar, Östberg, and Öxell 2015).

2.3.3 Cost-Benefit Analysis

Ecosystem services can be assessed using specific software, e.g., i-Tree, which can evaluate the urban forest using a cost-benefit ratio (Nowak et al. 2013; Grant 2015; Bodnaruk et al. 2017). The i-Tree suite of tools was developed by the U.S. Forestry Service and other collaborators to evaluate urban forest ecosystem services (USDA 2018b, a). There are, however, limits to the current software as it is not able to put a monetary value to some benefits, e.g., aesthetic beauty of a tree or the improvements in mental health associated with trees. In addition, the urban forest is not isolated and interacts with many other facets that make cost-benefit analysis difficult (Nowak and Dwyer 2007).

2.4 Urban Forest Assessment

Ecosystems services, as previously described, are affected by the dimension, structure, and health of the urban forest. To determine the ecosystem services and cost-benefit ratio of the urban forest, it therefore needs to be evaluated. A tree inventory is a record of assets (Wolowicz and Gera 2007) and a practical way of recording the individual tree attributes within an urban forest; it can also be an essential tool for urban forest management (Wood 1999; Wolowicz and Gera 2007). When assessing the urban forest four key questions need to be asked: (1) what is the area of study (street, park, City, etc.)? (2) are all the trees in the area to be studied (sample survey or exhaustive/complete survey)? (3) is only ground data, remote data, or a combination of both to be used for attribute/variable collection? and (4) what attributes/variables will be quantified? (Nowak 2008)

The following section will discuss the literature reviewed pertaining to the uses of GIS, remote sensing, and GPS technologies on urban forestry monitoring and management; it is divided into ground assessment and remote data assessment of the urban forest. Then I will specifically discuss urban forest analysis, then natural disaster and the urban forest.

2.4.1 Ground Assessment

Ground assessment is a survey of the tree population within an urban environment, which can range from a sample survey to a comprehensive tree survey

(Nowak et al. 2015). However, the practicalities of an urban environment mean that even a survey termed "comprehensive" will not be exhaustive as it is not always possible to evaluate trees on private land, if budgets are restricted, or practical to evaluate all trees within a given area.

Ground based urban forest attribute collection is the simplest way to get information, e.g., number of trees, species, diameter at breast height (DBH), condition, etc. Ground based surveys can be either based on sampling or a complete inventory (Wolowicz and Gera 2007; Nowak 2008) and can either collect in its basic form only tree numbers, e.g., windshield survey (Wolowicz and Gera 2007), or more attribute information. Nowak et al. (2015) in their paper "Simple street tree sampling" suggested that ideally a complete survey should be carried out as this provides data that is critical for management. If this is not possible, there are a variety of sampling procedures that can give generalized information regarding the urban forest; they also argued that the use of any tree sampling technique is better than not sampling the urban forest. However, there can be error with the survey if it is not complete. The size of the error depends on how many samples you undertake and can affect your ecosystem service evaluation.

GPS, in conjunction with GIS, has proved an invaluable tool when undertaking ground assessment of the trees within an urban forest (Ward and Johnson 2007; Hawthorne et al. 2015). The literature examined for the use of GPS/GIS in urban forest assessment is focused on three topics: the reasoning and specific methods for the use of GPS, the application of GPS, and the justification for the use of GPS for urban forest assessment and of ecosystem service determination.

For the reasoning and methods of using GPS, one paper detailed the difference in accuracy between Real Time Kinematic GPS (RTK GPS) and a Static GPS survey; the paper showed that not only are the accuracies comparable but that the work can be done in half the time using RTK GPS (Mekik and Arslanoglu 2009). In the second paper, Ward and Johnson (2007) looked at how GPS and GIS are used to manage urban forests by providing complex information in a format that is easily accessible.

Three papers reviewed the applications of GPS with GIS in three international locations. Two papers detailed the use and advantages of using GPS to locate boulevard trees in New Delhi, India (Ahmadzadeh et al. 2015) and Ibadan, Nigeria (Olokeogun, Akintola, and Abodunrin 2016) and one paper used GPS to map non-native invasive species in an urban forest in Atlanta, Georgia (Hawthorne et al. 2015). Of interest in this particular paper was the use of polygons to encapsulate large areas of invasive species rather than using points only (Hawthorne et al. 2015). Of note is the use of GPS and GIS in the global south (Ahmadzadeh et al. 2015; Olokeogun, Akintola, and Abodunrin 2016).

2.4.2 Remote Data Collection

Remote data collection or remote assessment, i.e., the use of remote sensing equipment, e.g., LiDAR, aerial photographic images, satellite data, etc., (Lillesand, Kiefer, and Chipman 2015) to collect tree attributes offers the potential for urban foresters and communities a way to collect data on a greater number of trees and hence generate a more comprehensive evaluation of the urban forest. This is particularly true with the reduction in cost of unmanned aerial vehicles and remote sensing equipment used with them.

2.4.2.1 Photographic Images and Optical Satellites

Aerial photography is the eldest, longest used, and temporally consistent form of remote sensing having initially been started by a photographer Gaspard-Félix who attached a camera to a tethered balloon taking a picture of Mal de Bievre an area close to Paris, France in the 1850s (Wulder 1998; Lillesand, Kiefer, and Chipman 2015). It has been used to determine landscape change in the USA since the 1930s (Morgan and Gergel 2010; Morgan, Gergel, and Coops 2010) and aerial photographic technology has subsequently changed over time with changes in radiometric properties, i.e., tone (greyscale) and color (Hue).

The literature reviewed on using photographic images to determine urban tree canopy assessment focuses on three topics: (1) comparison of aerial photographic image and remote sensing sampling methods to determine canopy cover; (2) different sampling approaches using aerial photographic images for canopy cover assessment; and (3) using aerial imagery to view historical canopy cover.

Five papers discussed comparisons between using aerial photography images and LiDAR and satellite imagery to assess canopy cover. In particular, three of these papers specifically compared aerial images to LiDAR. One paper created LULC classifications using OBIA; the last paper compared derived canopy cover assessment from the National Land Cover Database (NLCD) and photo images. Chen et al. (2017) showed that both LiDAR and aerial images had specific flaws and that the use of either technique was dependent on what questions were asked. Knight, Host, and Rampi (2016) used National Agriculture Imagery Program (NAIP) and LiDAR data to evaluate the canopy cover in the Twin Cities, MN; they showed that using OBIA for both images and LiDAR increases accuracy. However, there were challenges due to the large volumes of data. When using LiDAR, satellite and aerial photograph images, Ma, Su, and Guo (2017) found that all three were comparable for determination of canopy cover at a forest stand resolution; however, LiDAR proved more accurate for sparse or dense forest. Moskal, Styers, and Halabisky (2011) used hyperspectral resolution satellite images and photographic images with a resolution below 1m in conjunction with OBIA to create LULC classifications. They showed that the spectral content was more important than spatial content and, using OBIA, repeatable results were achieved. Nowak and Greenfield (2010) compared NLCD tree canopy cover estimates with photo interpreted estimates and showed that the NLCD derived data severely underestimates estimation of tree canopy cover compared to photo interpretation. Hyperspectral images have also been used to assess individual tree species and forest health (Voss and Sugumaran 2008; Thenkabail, Lyon, and Huete 2011). Further, the reducing cost of using unmanned aerial vehicles (UAVs) increases options for local data collection (Bahe 2018; Li et al. 2019).

Two papers detailed methods to analyze and deduce canopy cover extent from only aerial photographs. Nowak et al. (1996) detailed various methods to analyze aerial photographs, e.g., crown cover scale, dot method, and indicates their strengths and weaknesses, Ucar et al. (2016) compared two different sampling approaches (cluster sampling and random point based) to assess two different imagery sources (Google Earth and NAIP), for two similar sized US cities. The results showed that using both sampling approaches yielded similar statistical results as did using the different imagery sources.

2.4.2.2 Light Detecting and Ranging (LiDAR)

The literature on LiDAR, the urban forest canopy, and crown detection for individual trees concentrates on a select number of topics, focused on airborne discrete-return and waveform LiDAR. Discrete return LiDAR quantifies the time taken for either singular or multiple (2-5) laser pulse returns from a struck surface. In contrast, waveform LiDAR measures the complete variation in return time for each individual returned laser pulse (Lefsky et al. 2002; Sumnall, Hill, and Hinsley 2016). The literature concurred that both types of LiDAR or LiDAR in combination with other types of remote sensing data, e.g., hyperspectral images, etc., are becoming progressively significant in the evaluation of individual tree attributes and the urban forest structure.

Some papers focused on areas with no or limited structures, e.g., buildings, etc., such as forests, parks, or non-urban environments where the lack of structures allowed the researchers to concentrate only on the extraction of tree variable data (Lim et al. 2003; Chen et al. 2006; Omasa et al. 2007; Secord and Zakhor 2007; Tang, Dong, and Buckles 2013; Birdal, Avdan, and Türk 2017). Most papers reviewed concentrated on trees or urban forest within the urban environment. In contrast, the 3 papers on waveform LiDAR discuss forest variables, e.g., tree species classification within a forest environment not an urban forest (Yao, Krzystek, and Heurich 2012; Hovi et al. 2016; Sumnall, Hill, and Hinsley 2016)

Four papers referred specifically to the use of discrete return LiDAR to determine urban forest health within the urban environment (Shrestha and Wynne 2012; Zhang, Zhou, and Qiu 2015; Plowright et al. 2016; Song et al. 2016). Due to the restrictions of using discrete return LiDAR independently to determine the structure of the urban forest canopy, e.g., the complexity of isolating geometrically analogous trees and buildings from LiDAR data (Parmehr, Amati, and Fraser 2016), other papers discussed using LiDAR with different forms of remote sensing, e.g., hyperspectral data using algorithms to integrate the data (Voss and Sugumaran 2008; Zhang and Qiu 2011; Alonzo, Bookhagen, and Roberts 2014; Knight, Host, and Rampi 2016; Parmehr, Amati, and Fraser 2016).

Currently, there is a debate over the limits of LiDAR data (point clouds) for determining biophysical variables for trees, e.g., DBH. Shrestha and Wynne (2012) suggested that there were few experiments that derived biophysical parameters from LiDAR alone and in their research experiment they undertook the evaluation of biophysical parameters. Other studies since 2012 continue to use LiDAR with other remote sensing data, e.g., aerial imagery (Knight, Host, and Rampi 2016; Parmehr, Amati, and Fraser 2016) to define biophysical parameters. However, research using only LiDAR point clouds to estimate biophysical parameters continues (Li et al. 2012; Zhang, Zhou, and Qiu 2015; Zhen, Quackenbush, and Zhang 2016; Lindberg and Holmgren 2017).

2.5 Urban Forest Analysis

2.5.1 Object Based Image Analysis

From a remote sensing perspective, the urban forest canopy can be viewed as just one type of land cover category. Information from remote sensing systems can be stored either in an analog or digital form (Wang and Weng 2014) and the basic unit of a digital image that is a representation of a category, e.g., urban forest canopy, is a pixel (Wulder 1998; Lillesand, Kiefer, and Chipman 2015; Tewkesbury et al. 2015). The literature states that, historically, the major method to extract LULC data from remote sensing digital imagery, i.e., satellite or digital/scanned aerial photography, is through the utilization of per-pixel based classification methods (Moskal, Styers, and Halabisky 2011; Hussain et al. 2013; Li and Shao 2014).

Per-pixel based methods do have limitations particularly with high resolution satellite and aerial photographic images. For example, Yu et al. (2006), Meneguzzo, Liknes, and Nelson (2013), Li and Shao (2014), and Pu, Landry, and Yu (2018) detail the “salt-and-pepper” effect caused by increased spectral variance within a designated LULC class caused by the increase in the number of pixels per unit area. This problem is compounded for the urban environment due to the complex nature of the spectral domain in this setting (Zhou and Troy 2008; Myint et al. 2011).

OBIA is an alternative method to per-pixel based LULC extraction. Unlike per-pixel extraction, which predominantly uses spectral variance of pixels, OBIA uses a potential combination dependent on algorithms of spectral, shape, spatial, textural, contextual, and topological attributes of a set or patch of pixels (Walker and Briggs 2007;

Hay et al. 2008; Blaschke 2010; Moskal, Styers, and Halabisky 2011). Due to OBIA's ability to extract LULC using multiple attributes, it is ideally suited to analyze changes to high resolution, temporally changing photographic images (Walker and Briggs 2007; Morgan, Gergel, and Coops 2010; Moskal, Styers, and Halabisky 2011; Meneguzzo, Liknes, and Nelson 2013; Morgan and Gergel 2013).

2.5.2 i-Tree Software

Walton, Nowak, and Greenfield (2008) are credited for the creation of the USDA Forest Service's i-Tree Canopy. In their 2008 paper, they discuss the use of random sampling and associated computation of standard error as a tool to photointerpret digital orthophotographs to determine forest canopy cover.

Four other papers also explicitly mentioned the U.S. Forestry Service's i-Tree as the preferential software system to determine ecosystem services (Nowak et al. 2013; Grant 2015; Strunk et al. 2016; Bodnaruk et al. 2017). Two papers used the i-Tree model to predict where trees need to be planted (Grant 2015; Bodnaruk et al. 2017) and Strunk et al. (2016) used the USDA Forest Service's Forest Inventory and Analysis (FIA) program to observe urban plots, differentiate the urban forest, then used i-Tree to estimate the data to be added to an urban tree inventory.

2.6 Uncertainty, Error Assessment and Validation of Land Cover/Land Use Classes

A fundamental component for the ability to use assigned LULC is the validation that the assigned class is indeed correct and in the precise location (Walton, Nowak, and Greenfield 2008). Richardson and Moskal (2014) discussed uncertainty in urban forest canopy assessment by using Seattle, WA, USA as a case study and by comparing historical canopy assessments methods with their own. The paper clarified the need for error assessment, either quantitative or qualitative, if canopy cover assessment is to be viewed over time.

Congalton and Green (2019) define qualitative error assessment as does the map “look good” and suggest two methods: similarity analysis and an error budget to provide additional error criteria of the map. Quantitative error assessment can be divided into positional and thematic assessment. Positional accuracy determines if the defined objects (LULC) are in the precise location and thematic accuracy determines if the correct LULC has been determined for the precise location (Wang and Weng 2014; Lillesand, Kiefer, and Chipman 2015; Congalton and Green 2019).

In validation assessment it is also crucial that the appropriate sampling unit, e.g., pixel, sets of pixels, or polygon, is used for the appropriate LULC extraction software (Chen et al. 2017; Congalton and Green 2019) and that human bias regarding interpretation also needs to be acknowledged and accounted for (Hoffman and Markman 2001).

2.7 Natural Disaster and the Urban Forest

Finally, the literature with respect to the use of remote sensing and/or ground assessment to determine and categorize the effect of tornados and tree diseases on the urban forest and its effect on ecosystem services were reviewed.

2.7.1 Tornados

The tornado literature can be divided into four groups. First is the use of aerial and ground photographic images to describe and classify tornado types based on damage, i.e., Fujita (EF) scale (Fujita 1971). Second is the identification of tornados (not land use specific); these papers use a combination of Synthetic Aperture Radar (SAR) and/or multispectral satellite imagery, then use per-pixel methods to extract LULC change, e.g., creating a normalized difference vegetation index (NDVI).(Yuan, Dickens-Micozzi, and Magsig 2002; Gokaraju et al. 2015; Kingfield and de Beurs 2017). Third, three articles specifically use aerial photographic images to assess damage associated with tornados. One paper analyzes photographic images to view the widespread damage that occurred on May 20th, 2013 tornado in Moore, Oklahoma, USA (Burgess et al. 2014). Karstens et al. (2013) utilize aerial photographic images to digitize the direction trees fell in the tornado event and compare this to computational simulations of tree falling directions based on the wind direction for tornado damage in Missouri and Alabama. Bloniarz and Brooks (2011) detail how the 2011 tornado in Springfield, MA effected the residential boulevard street tree canopy cover and the subsequent effect on the temperature and humidity in that area. Finally, two papers discussed the modeling and reconstruction of tornados within a forested landscape (Holland, Riordan, and Franklin 2006; Beck and Dotzek 2010).

2.7.2 Tree Diseases

2.7.2.1 Emerald Ash Borer

Tree diseases can have a significant impact on the forest and urban forest as has been recently witnessed by the epidemic of the mountain pine beetle (Dendroctonus ponderosae) within the Black Hills, South Dakota (Mullen, Yuan, and Mitchell 2018) or the introduction of the non-native EAB (*Agrilus planipennis;* Fairmaire (Coleoptera

Buprestidae)) (Figure 2) throughout the eastern and mid-western states. With particular emphasis on the urban forest, the non-native invasive beetle, EAB was first discovered in Michigan and Ontario in 2002 (Mercader et al. 2009; Siegert et al. 2011; McCullough and Mercader 2012). Since 2002 it has spread to more than twenty states and two Canadian provinces (Muirhead et al. 2006; Anderson and Dragićević 2015; Fahrner et al. 2017). EAB larvae feed on the phloem of the four main ash tree species (*Fraxinus* spp.) found in the USA: white ash (F. *americana)*, black ash (F. *nigra)*, green ash (F. *pennsylvanica*), and blue ash (F. *quadrangulate*) (BenDor and Metcalf 2006). As the density of the population of larvae increases, more phloem is consumed resulting in the eventual death of the ash tree (McCullough and Mercader 2012; Cuddington et al. 2018); in Michigan, death rates for ash are 99% (Spei and Kashian 2017). With the exception of blue ash which is showing some resistance to EAB (Davidson and Rieske 2016; Hauer

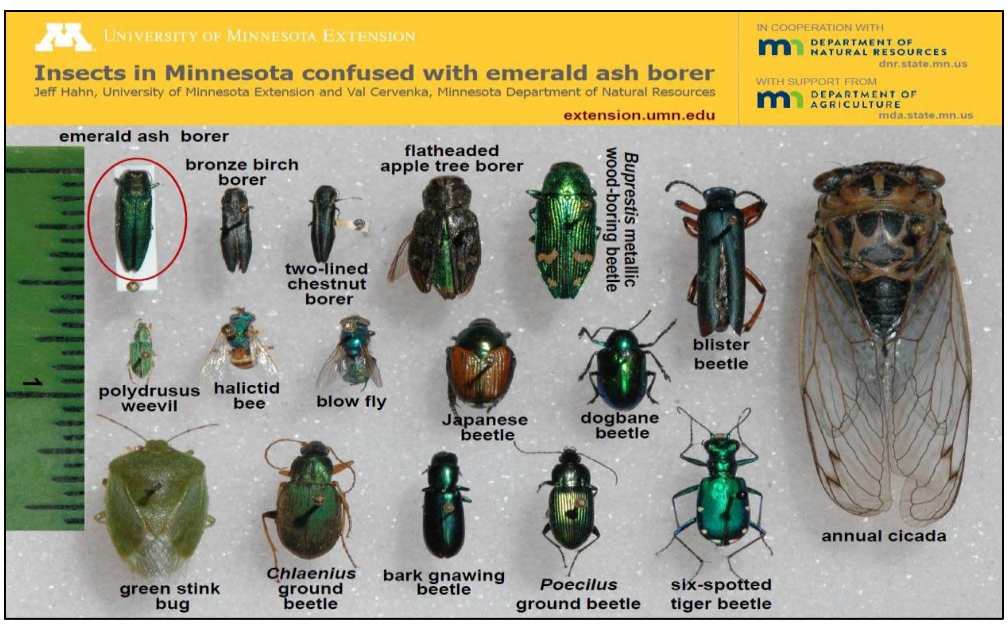

Figure 2. Emerald Ash Borer beetle identification poster (MNDNR 2019a)

and Peterson 2017; Spei and Kashian 2017), ash trees have no natural defenses and there are no native enemies to protect against EAB (Davidson and Rieske 2016). The total monetary and environmental services cost across the USA associated with EAB is colossal with totals exceeding $300 billion (Muirhead et al. 2006; Prasad et al. 2010; Hauer and Peterson 2017).

Historically within the Midwest there have been two other tree diseases that have affected the urban forest. The butternut (*Juglans cinerea L*.) and particularly the American elm (*ulmus americana L*) trees were both highly visible within the urban forest (Townsend, Bentz, and Douglass 2005) and naturalized areas prior to the 1980s but due to DED (*Ophiostoma ulmi* and *O. nova-ulmi*) and Butternut Canker (*Sirococcus clavigigenti-juglandacearum*), they have with the exception of a few disease resistant "survivor" trees disappeared from the landscape.

2.7.2.2 Dutch Elm Disease

DED is caused by the fungus *Ophiostoma ulmi* and *O. nova-ulmi and i*s transmitted from an infected tree to a non-infected tree by the elm bark beetle (Scolytus) (Brasier and Buck 2001). Figure 3 illustrates the effects of the fungus on the leaves. There were two pandemics associated with DED; the first occurred in Europe during the 1930s the second occurred during the mid-1970s; at this point the USA was already heavily infected with Minnesota's initial infection being in 1961 (Strobel and Lanier 1981; Brasier and Buck 2001). The number of trees lost nationally since the 1970s is estimated to be in the hundreds of millions and in Minnesota, the City of Minneapolis now has a fraction of the City's estimated 200,000 pre-DED elm trees (Giblin and Gillman 2009).

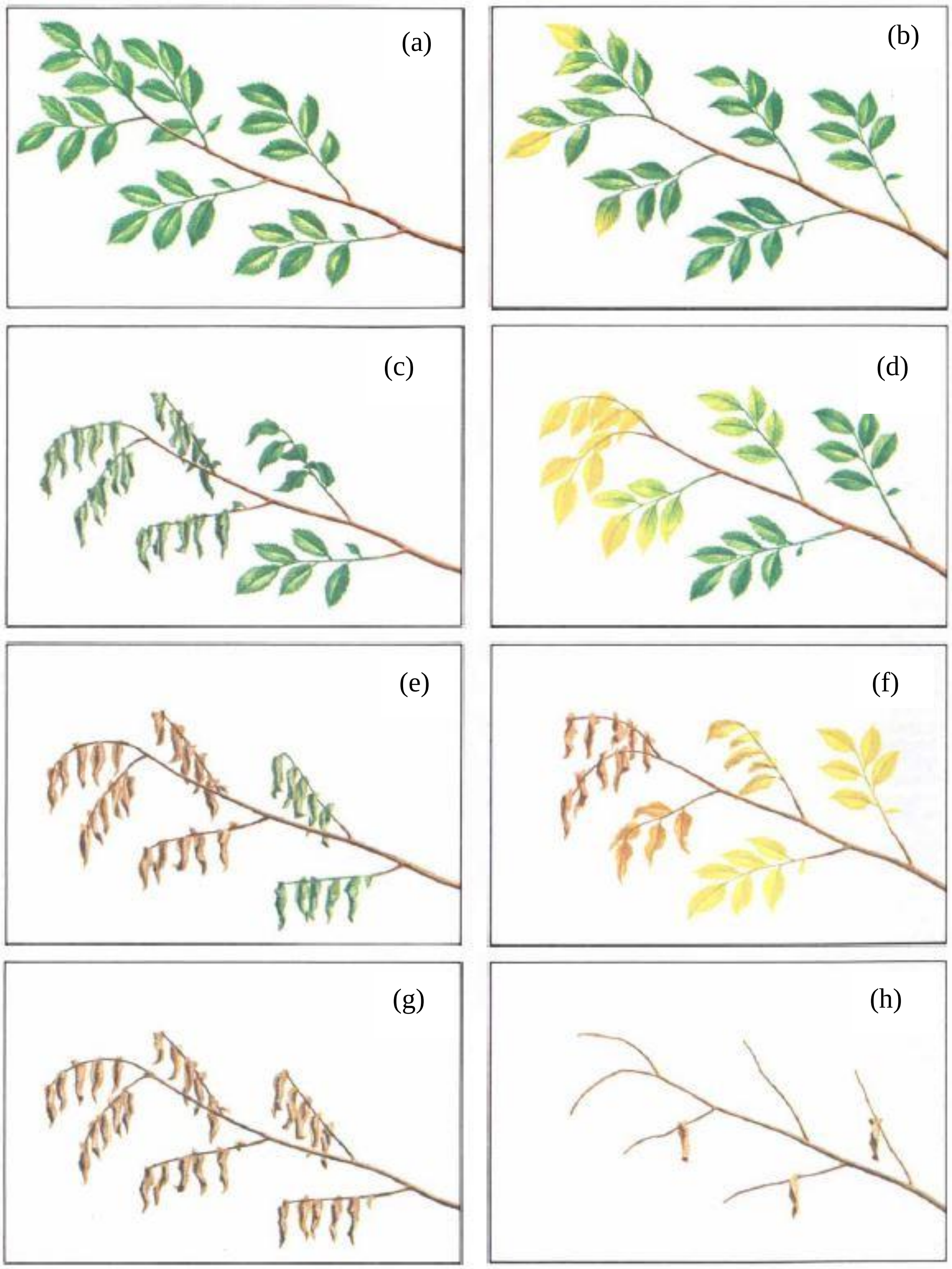

Figure 3. An illustration (a-h) showing the progressive symptoms of Dutch Elm Disease on tree leaves (Strobel and Lanier 1981)

2.7.2.3 Butternut Canker

The butternut tree unlike the American elm was not as populous within the forest and urban forest; however, its demise due to butternut canker is still important with respect to tree diversity and canopy cover. The pathogen was first reported in the USA in Wisconsin in 1967 (Broders et al. 2015). Like DED it is a fungal disease (Figure 4) that can spread using vectors such as beetles or infected seeds and rain splashes (Broders et al. 2015). In 1992, Minnesota was the first state to actively protect the butternut tree (Ostry and Woeste 2004); however, since the 1980s it is estimated that the population of butternuts within the USA has decreased by 58% (Morin et al. 2018).

Figure 4. Symptoms of butternut canker on trunk (a, b); stem (d) caused by fungus (c) (Broders et al. 2015)

2.8 Conclusions

The literature has shown that the ecosystem services provided by the urban forest are measurable and beneficial to the urban environment. To ascertain all of the potential ecosystem services an accurate description of the urban forest needs to be provided. Ground based data (complete tree inventories) is the most accurate way to collect data on the urban forest, however, it is time consuming, expensive, and it is often impractical or illegal to collect data on all of the trees within the urban forest, e.g., getting access to trees in backyards or in naturalized areas. Remote sensing offers advantages for collecting data as it is collected remotely and on a large scale giving an urban forester access to previously inaccessible information.

Ground assessments and remote sensing tools each have has pros and cons depending on, for example, the spatial resolution needed for a given variable. Another limiting factor in assessing the urban forest is cost. For example, high resolution remote sensing data can be expensive, as is the hardware to store the large amounts of data, but this needs to be weighed against the cost of a complete ground assessment. In addition, often ground-based data is needed in conjunction with remote sensing data because of the limitation of extracting individual trees from satellite data. It is also important to be aware of any limitations of using a survey technique or combination of techniques when assessing the urban forest.

With respect to natural disasters within the urban forest, remote sensing in all its forms has proved instrumental in tornado classification and also in the determination of damage associated with tornados in a variety of land classes including the urban forest.

The literature review has also shown the impact that tree diseases can have on tree diversity and the forest/urban forest structure, e.g., canopy size.

3. Data and Methodology

3.1 Data

The data for the thesis was acquired from a variety of sources. It consists of digital ortho-images, unrectified aerial images, scanned images and historical maps, vector data, and LiDAR data. Tables 4 and 5 provide detailed information regarding the multi-source datasets.

3.1.1 Photographic Image Selection Criteria

A large amount of aerial photographic images was surveyed to determine the best images to extract the urban forest canopy cover. As the research is based on a historic assessment, both panchromatic and color images were reviewed; it was important to maximize canopy cover extraction and to be consistent with the monthly variation in urban tree leaf area/canopy cover. The choice of aerial photographic images used to extract urban forest canopy cover was based on seven selection criteria: (1) high image resolution, i.e., 600 DPI or pixel resolution 3.06 ft or greater; (2) minimum map scale of 1:20,000; (3) trees with leaf on; (4) historical photographic images preferentially taken during the same months; (5) images should contain the full areas within the City of St Peter boundary of 1928 and 2017; (6) ease of access to and availability of images; and (7) access to images just prior to and post 1998 tornado, to assess the impact of the tornado on the urban forest canopy cover. Using these criteria, multi-temporal photographic images were selected for 1938, 1951, 1964, 1995, 2008, and 2017 (Table 4).

Table 4. Photographic images & Map datasets acquired for this study

Data Type	Source	Date of Image	File Type	Coordinate System	Resolution/Scale
Hardcopy Historical Engineering Map	City of St Peter, Engineers Office, MN	1928	.tif	NAD_1983_HARN_Adj_MN_Nicollet_Feet	600 DPI/1:500
Hardcopy Historical Aerial Photograph	City of St Peter, Engineers Office, MN	July-August^/ 1995	3-band, natural color/.tif	NAD_1983_HARN_Adj_MN_Nicollet_Feet	600 DPI/1:600/3.06 ft
Digital NAIP Vertical Aerial Photographs	Minnesota Historical Aerial Photographs Online (MHAPO)	July/ 1938	Panchromatic/ .jpg	NAD_1983_HARN_Adj_MN_Nicollet_Feet	600-1200 DPI/1:20,000/3.06 ft
		July/ 1951	Panchromatic/ .jpg	NAD_1983_HARN_Adj_MN_Nicollet_Feet	600-1200 DPI/1:20,000*/3.06 ft
		July-August/1964	Panchromatic/ .jpg	NAD_1983_HARN_Adj_MN_Nicollet_Feet	600-1200 DPI/1:20,000/3.06 ft
	United States Geological Survey (USGS)	July/ 2008	4-band; color near infrared/Geo Tiff	NAD_1983_UTM_15N	3.06 ft
		August/ 2017	4-Band; color near infrared/Geo Tiff	NAD_1983_ UTM_15N	3.06 ft
i-Tree Canopy Aerial Photographs	United Department of Agriculture (USDA) Farm Service Agency	2008/ 2019	N/A	N/A	3.06 ft

*No Scale shown on photographic image or within metadata from MHAPO or MNDNR. Assumption of scale based on 1938 and 1964 images that show scale within photographic image.
^No data shown for month image captured. Visual interpretation indicates image captured July-August.

Table 5. Vector and LiDAR datasets acquired for this study

Data Type	**Description**	**Source**	**Date**	**File Type**	**Coordinate System**	**Resolution/ Scale**
Vector Data	City of St Peter Roads	Nicollet County, MN	2017	.shp/Line	NAD_1983_HARN_Adj_MN_Nicollet_Feet	N/A
	Nicollet County Tax Parcel data	Nicollet County, MN	2017	shp/Polygon	NAD_1983_HARN_Adj_MN_Nicollet_Feet	N/A
	Nicollet County City Limits	Nicollet County, MN	2017	.shp/Polygon	NAD_1983_HARN_Adj_MN_Nicollet_Feet	N/A
	Tornado Tracts	National Oceanographic & Atmospheric Administration (NOAA)	1950-2017	.shp/Line	GCS_North_American_ 1983	N/A
LiDAR Data	LiDAR Point Cloud	Minnesota Department of Natural Resources (MNDNR)	2010	.laz	NAD_1983_UTM_Zone_15N	Resolution/ Nominal Pulse Spacing (ft) = 4.25
Specific LiDAR collection information	Data collected in leaf-off periods, April 8-May 5 & November 2-19, 2010, via fixed-wing aircraft equipped with LiDAR system (Optech Gemini) including differential GPS unit and inertial measurement system. Area data horizontal positional accuracy: acquired at or below 5,577.43 ft above mean terrain with horizontal accuracy of 1 in. Vertical Positional Accuracy values (RMSE): better than 3.94 in. Fundamental Vertical Accuracy of the Classified Bare Earth: 0.03 in at 95% confidence level in the 'Open Terrain' land cover category. Diminished accuracy expected in areas of dense vegetation due to fewer points defining bare earth in those areas (MnGeo 2010).					

3.2 Methodology

To aid in clarifying the methodological process, see Figure 5. Each stage of the methodology shown in the schematic, apart from the results, is discussed within this section.

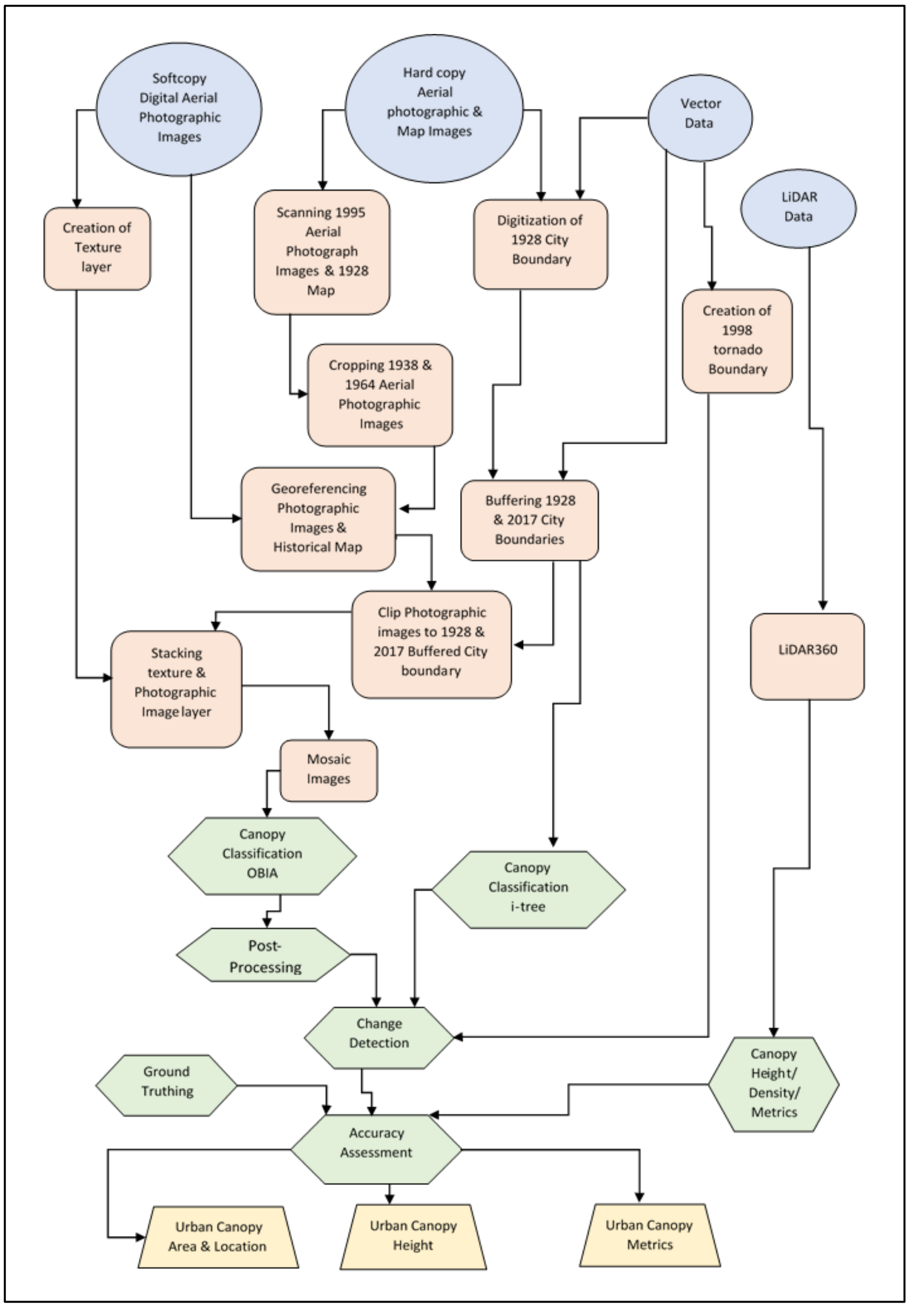

Figure 5. Methodology schematic

3.2.1 Photographic Image and Historical Map Analysis Preparation

Before the analysis of the images could take place, a series of image preparation steps was necessary.

First, to facilitate georeferencing and analysis, the 1938 and 1964 panchromatic images were cropped using .jpg lossless cropping tool, within IrfanView's image manipulation software (Skilijan 2019) to remove black borders and sections of the image that were distorted, e.g., incorrect tone, and deemed unusable for analysis.

Second, both the 1995 aerial photo and the 1928 engineering map were hard copy versions. To create soft copy versions both images were digitally scanned using Hewlett Packard DesignJet T2530 digital scanner. The images were scanned at 3-band, natural color at 600DPI and stored as .tif files.

Third, the NAIP georeferenced imagery from 2008 and 2017 and the 1951 (North) MHAPO were downloaded. It was not possible to ascertain if the 1938, 1951 (South), 1964, and 1995 aerial photographic images were orthorectified and it was not possible to orthorectify them as there was no available data regarding camera parameters (Yuan 2008). In addition, the 1938, 1951, 1964, and 1995 aerial photographic images and the 1928 engineers map did not have exterior orientation parameters (Lillesand, Kiefer, and Chipman 2015) associated with the data. Therefore, the photographic images and map were georeferenced (Lillesand, Kiefer, and Chipman 2015) using image to map geometric transformations (Rees 2013; Chang 2016) within ArcGIS 10.5. Table 6 shows the detailed information about the georeferencing.

Table 6. Georeferencing information

Image type	Year Of Image (Compass location)	Reference Data: Aerial Photo 2017 Roads (.shp) used for all	Total Root Mean Square Error (RMSE) (ft)
Aerial Photo	1995	2017 NE, NW & SW	20.34
	1964 (SW)	2017 NE, NW & SW	36.91
	1964 (SE)	2017 NE, NW & SW	10.03
	1964 (N)	2006 NE/2017 NE, NW & SW	72.80
	1951 (N)	2006 NW & SW	N/A
	1951 (S)	2006 NW& SW/1951 N	273.52
	1938 (NE)	1951 S & N	22.24
	1938 (NW)	1938 NE/1951 S & N	4.58
	1938 (S)	1938 NE & NW/1951 S	13.83
Engineering Map	1928	1951 S & N	372.70

The RMSE ranges from 4.58 ft to 372.70 ft; on average 17 ground control points (GCPs) were used. Relatively high RMSEs were found for the 1951 and 1928 engineering map. The 1951 (South) photographic image with an RMSE of 273.52 ft was georeferenced using a 1st order polynomial transformation with 30 GCPs. The 1928 engineering map had a RMSE value of 372.70 ft; it was georeferenced with 9 GCPs with a 1st order polynomial transformation. The GCPs were based on a reference photograph from 1951, which was better suited as a reference than the 1938 photograph due to difficulty in determining viable GCPs in 1938. The high RMSE is likely due to the limited GCPs available, which were based on the road layout; it is also probable that the road layout has changed between 1928 and 1951. For example, the St Peter Broadway Bridge located on highway 99 was remodeled in 1931 (MNDOT 2006), three years after the 1928 engineering map was created, therefore the road layout detailed in 1951 is likely to have moved leading to a change in road location that cannot be verified.

Due to the disparity in image type, location of suitable GCPs for overlapping and adjacent images, limited availability of GCP sites, and temporal variation of the photographic images when georeferencing, the process for accuracy of individual images was based on a compromise between both RMSE and visual interpretation. It should be noted that there are a variety of methods to assess error, e.g., Mean Absolute Error (MAE) (Li et al. 2019). Low RMSEs do not guarantee positional accuracy (ESRI 2019).

Once the 1928 City of St Peter Engineering map had been georeferenced, the City limits were digitized from the 1928 engineering map, thus creating a polygon feature class. The 1928 and 2017 feature class boundaries were then given a buffer of 200 ft. The buffer was created for two reasons. First, the City of St Peter boundary is a human construct but the urban forest and individual trees do not readily conform to strict linear form as a boundary. As the city forester for St Peter for 13 years, my personal observations and research dictates that it unlikely that any trees in the boundary areas will have a canopy width greater than 400 ft therefore the 200 ft buffer will contain those trees that are within the boundary of the City. Second, the 200 ft boundary and the remaining minimum bounding rectangle outwith the 1928 and 2017 City boundary is a large enough area to perform validation results on the aerial photographic images.

The analysis to determine the urban forest canopy cover took place within the City of St Peter boundary of 1928 and 2017. The aerial photographic images analyzed are far larger than the boundary. Therefore, to reduce the processing and analyzing time, the aerial photographic images were clipped to the 1928 and 2017 City of St Peter polygon feature classes. No options were used within the clip and the minimum bounding rectangle was used so as not to affect image pixel values (ESRI 2019).

After consultation with William Veteto (Veteto 2019a) at Overwatch Systems, Ltd, Feature Analyst, Technical Support, it was recommended that to effectively and efficiently analyze the aerial photographic images using OBIA it would be prudent to combine the images to form a single raster dataset. To achieve this all clipped aerial photographic images were mosaicked. The mosaic operators used were dependent on the visual quality and pixel value of the overlapping sections of aerial photographic images; therefore the order of rasters was based on these variables (ESRI 2019).

In order to aid discrimination between classes for the panchromatic and 1995 three band color image, a 3 x 3 variance (2^{nd} order) texture layer was created from the mosaicked photographic images within ERDAS IMAGINE 2018 (Yuan 2008). Once the texture layer was created, each texture layer was stacked with the applicable mosaicked photographic image.

3.2.2 Creation of 1998 Tornado Boundary

As detailed previously, the tornado that swept through the City of St Peter between 17:18hrs and 17:36hrs on 29 March, 1998 may have had a profound effect on urban forest canopy cover extent. To verify the area and direction of the tornado to compare with the analyzed aerial photographic images, data was acquired from NOAA Storm Prediction Center's (SPC) United States severe report database (NOAA 2017). The data extracted was two polyline shapefiles that were buffered to a distance of 2200 yds and clipped to the 1928 and 2017 boundary to reflect the geographic extent of the tornado for the research area as described by the SPC (NOAA 2017).

3.2.3 Urban Forestry Canopy Extraction using Object Based Image Analysis & Change Detection

There is a variety of open source, freeware, and commercially available OBIA software programs (Table 7) (Baisantry, Shukla, and Bansal 2017).

Table 7. Comparison of OBIA software

Software	Developer	Algorithm	Availability	Formats
eCognition	Definiens Imaging	Multi resolution	Commercial	Raster, Vector
Feature Analyst*	Overwatch Systems Ltd.	Artificial neural networks, Decision trees, Bayesian learning, K-nearest neighbor	Commercial	Raster, Vector
Bastik	Uni. Of Eidelberg	Watershed	Open-Source	Raster
Multispec	Purdue University	Clustering	Freeware	Raster
SPRING 4.0	INPE, Brazil	Region Growing	Freeware	Raster,
Orfeo	CNES	Watershed Mean shift Edison	Open Source	Raster, Shape
ILWIS	ITC	Clustering	Open Source	Raster

(adapted from Baisantry, Shukla, and Bansal (2017))
*(Opitz and Blundell 2008)

Feature Analyst was used for the OBIA analysis for a variety of reasons in comparison to the other OBIA software. Research has shown that for analyzing high resolution panchromatic aerial photographs, texture can be crucial to maximizing extraction of land use categories particularly forest and urban forest areas (Haralick, Shanmugam, and Dinstein 1973; Ryherd and Woodcock 1996; Yuan 2008). This is due to panchromatic photographs having low radiometric and spectral information and texture adds another variable to aid extraction (Yuan 2008). Unlike other OBIA software, e.g., eCognition, Feature Analyst includes texture as one of their object inputs (Nagel, Cook, and Yuan 2014); the combination of using both the texture layer created in ERDAS IMAGINE 2018 as a reflectance band and that included within Feature Analyst gave the best results. In addition, Feature Analyst, unlike other OBIA software, is an automated feature extraction software program (Blundell et al. 2008; Opitz and Blundell 2008) that uses a contextual classifier in its segmentation process which utilizes object size, edge type, spatial context, and shape to produce vector files that can be edited (Opitz and Blundell 2008; Nagel, Cook, and Yuan 2014). The program also uses hierarchical learning to eliminate false positives thereby mitigating and improving the speed of clutter removal (Opitz and Blundell 2008; Yuan 2008). For more information regarding Feature Analyst analysis processes see O'Brian (2003); Opitz and Blundell (2006); Blundell et al. (2008); Yuan (2008); Olowokudejo and Piwowar (2013); Nagel, Cook, and Yuan (2014); Byholm (2017). Feature Analyst was also software that I had access to and familiarity with.

This project is primarily concerned with the extraction of the urban forest. However, after preliminary investigations using Feature Analyst, it became apparent that the extraction classification process was most effective if supervised learning using multiple categories (classes) (Overwatch Systems Ltd 2013) were extracted rather than unsupervised or a single class approach, i.e., the created urban forest polygons were more accurate with less clutter. Therefore, the classes in the following table were used (Table 8).

Table 8. Description of Land Class

Class	Description	Areas
Urban Forest	Tree and shrub canopy	Boulevard, Gardens, Naturalized areas
Water	River, Ponds, Storm Water basins, Swimming pools, etc.	MN River, Gardens, City Property
Impervious Surface	Roads, Buildings, Parking lots, etc.	Urban & Rural
Grass/Soil	Agriculture land, Gardens, Green spaces, Fields, Gravel roads, etc.	Boulevard, Gardens, Naturalized areas, Parks
Shadow/Other	Buildings, trees, bridges, etc.	Urban & Rural

Large shrubs have been included within the urban forest, as it is virtually impossible to differentiate between trees and large shrubs in the panchromatic images due to the resolution and hue/tone. It also became apparent, as documented by Yuan (2008), that differentiation between grass and soil in the panchromatic images was challenging, consequently the classes were combined to one group Grass/Soil. For consistency these classes were kept for panchromatic, 3-band natural color, and 4-band color infrared images.

All the images had some form of shadow, e.g., buildings or trees, etc., associated with them; Yuan (2008) resolved this issue by using stacked NAIP and Quickbird images to produce a seven band image with differing shadow directions for the same locations. It was not possible to obtain other high resolution images for the time periods used within this research, therefore a shadow/other class was created as detailed in Qiu, Wu, and Miao (2014). In addition, for the 1995 scanned image a mask using pixel values of 0 was used to remove shadow areas.

As detailed in Qiu, Wu, and Miao (2014) and Nagel and Yuan (2016), the training samples were manually digitized drawing close to the edge of class features (objects) so as to represent the shape, size, spectral content, texture, patterns, and contextual data from adjacent objects. This allows the Feature Analyst template matching method to be its most successful.

Due to the differences between the three types of aerial photographic images, different histogram stretches, learning options, and input representations were utilized, e.g., spatial context and Bullseye 4 (Overwatch Systems Ltd 2013), to extract each class from each image. For each image, multiple supervised learning operations were repeated until optimum class classification was reached. Once achieved, the results were repeatedly refined using the Removing Clutter tool (Yuan 2008; Overwatch Systems Ltd 2013) until the final class polygon shapefile was created.

Post-processing of the OBIA data was performed first in ArcGIS by visibly comparing the OBIA canopy cover class polygons to their photographic images and removing inaccuracies. Second, the OBIA polygon was converted to raster and imported into ERDAS IMAGINE 2018 where a majority function using a 3 x 3 window was used to isolate and remove single pixels incorrectly classified as canopy cover.

To quantitatively determine and compare canopy cover change between the various research years, a post classification change detection model was created within ERDAS IMAGINE 2018 (Yuan et al. 2017). This was achieved by converting the polygon output files from Feature Analyst to rasters; once created, a change detection model was employed to create a thematic layer from a matrix that evaluated two historical image files. The newly created thematic layer displays the unique difference in values of the two original images overlapping (Hexagon Geospatial 2019b).

3.2.4 Accuracy Assessment of Urban Forest Canopy Cover Extraction using OBIA

A site specific thematic error matrix (Congalton and Green 2019) and Kappa Coefficient were created for the accuracy assessment; they were generated using ERDAS IMAGINE 2018 (Zhou and Troy 2008). Stratified random sampling was used so that each class was proportionately weighted; this was necessary as there are few canopy class features and they are not uniformly distributed (Qiu, Wu, and Miao 2014).

To select the reference pixels, ERDAS IMAGINE 2018 uses a square window; the user can define the number of pixels used within the window (Hexagon Geospatial 2019a). To mitigate against potential positional inaccuracy, a small difference in cell size between photographic images of different years, and ensure a representative sample within a category polygon (Congalton and Green 2019), a sample unit of a 5x5 pixel block was created for each year. Congalton and Green (2019) state that when the research site is less than 1 million acres and 12 classes, a minimum of 50 samples per class is needed for accuracy assessment. Therefore, 150 samples were used: 50 per class (canopy, non-canopy) and 50 randomly distributed. As there were no higher resolution images available for reference data, the reference images used within ERDAS IMAGINE were the same aerial photographic images used to extract the classifications.

As this research is an historical assessment, field sample collection was only possible for the 2017 dataset. The area selected for field sample data was based on the ability to legally and practically assess areas within the 2017 St Peter boundary. The areas selected were the City of St Peter owned land (parcel), and the right of ways (ROW) of all roads within the St Peter boundary (Figure 6).

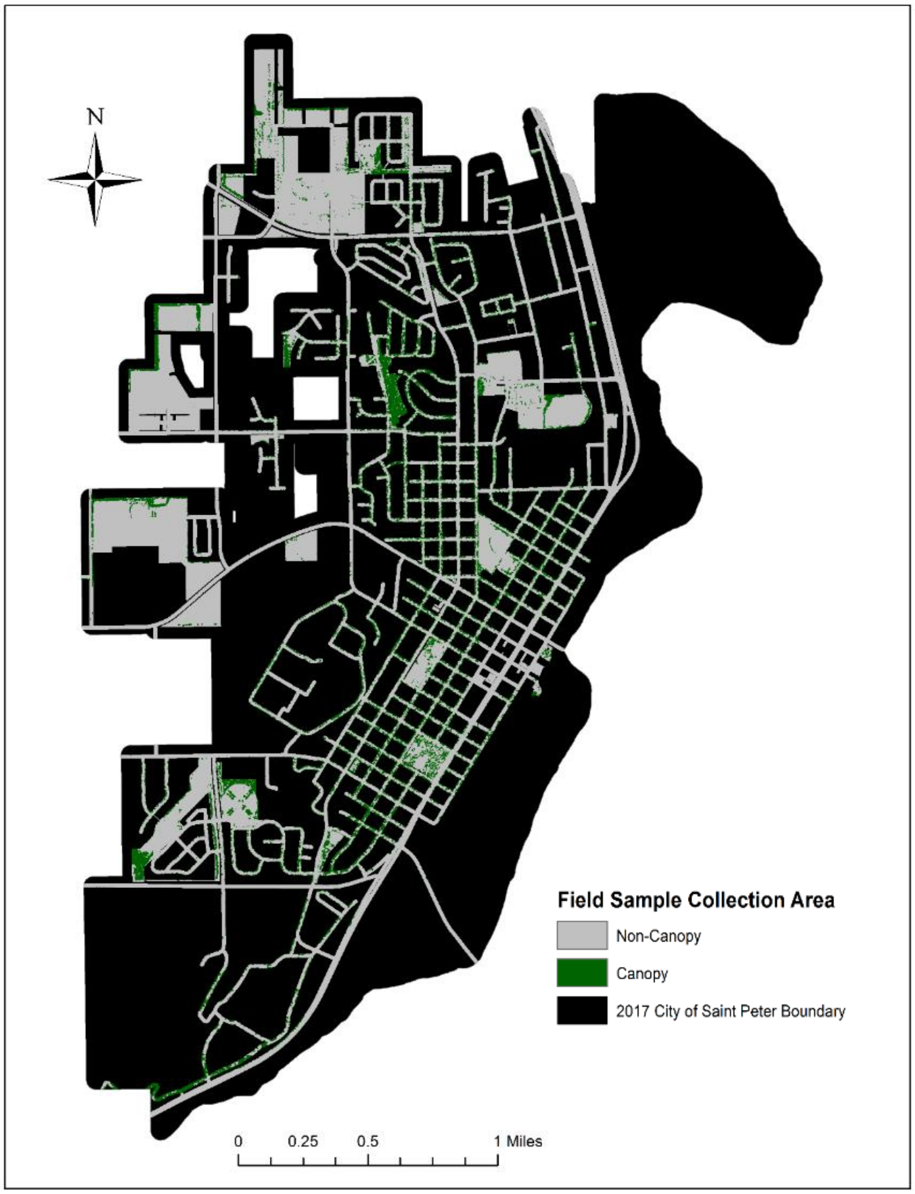

Figure 6. Map of field sample collection area within the City of St Peter

Because of flooding along the Minnesota River Valley flood plain in September 2019, the field sample map was modified and stratified random points created in those areas that were practical to assess. The field sampling map was created in ArcGIS by buffering the Nicollet County streets shapefile to reflect the correct ROW distance for streets within St Peter, i.e., 80 ft or 120 ft dependent on municipal code. This dataset was then merged with the St Peter tax parcel polygon shapefile minus those areas inaccessible due to flooding. The 2017 (2017 boundary) OBIA canopy change raster was clipped using the merged shapefile. The raster was then imported into ERDAS IMAGINE 2018 where sample point creation was based on the protocol as described for photo-interpretation accuracy assessment. The field sample data was collected in September 2019, utilizing a portable laptop with ESRI ArcMap 10.6, NAIP 2017 photographic image, City of St Peter streets feature class and the 150 stratified random point locations installed. The sample sites were accurately located and delineated using verifiable and recognizable landmarks both on the 2017 NAIP photographic image and in the field (Congalton and Green 2019). Due to the researcher's in depth knowledge and experience of land use and land cover change, as the City Forester for the City of St Peter, any difference between the 2017 photographic image and 2019 ground truthing were mitigated.

3.2.5 Urban Forest Canopy Extraction using i-Tree Canopy

i-Tree is a suite of urban forest ecosystem service evaluation software tools that are freely available. They were created and developed by the U.S. Forestry Service and other collaborators (USDA 2018a, b). i-Tree Canopy is one tool within i-Tree that allows users to precisely define land cover categories (e.g., trees, water, impervious surfaces) by using web browser applications Google Maps and Google Earth to allow photo interpretation of current and historical aerial imagery using randomly selected points (USDA 2019). The only photographic image available in Google Maps was 2019 and the only historical relevant image in Google Earth was 2008.

The following steps were used to create land cover estimates for both the 1928 and 2017 City of St Peter boundaries using Google Maps or Google Earth Images. The dates of the images used are listed in the Table 9.

Table 9. Google Earth image data

City Boundary Date	Land cover classification	Google Maps and Google Earth Image Date	Google Earth Image supplier
1928 City Boundary	Urban forest, Water, Impervious surface, Grass/Soil, Shadow/Other	2019, 2008	United Department of Agriculture (USDA) Farm Service Agency
2017 City Boundary	Urban forest, Water, Impervious surface, Grass/Soil, Shadow/Other	2019, 2008	USDA Farm Service Agency

Both 1928 and 2017 polygon City of St Peter boundary shapefiles were imported into i-Tree Canopy and five classes (Urban forest, Water, Impervious Surface, Grass/Soil, Shadow) as per OBIA forest canopy assessment were created. Employing the 2019 Google photographic image in Google Maps, one thousand randomly generated survey points were produced and using photo-interpretation, a class was assigned to each point within the boundary areas as recommended by i-Tree Canopy Technical Notes (USDA 2011). For photo interpretation of the 2008 Google Earth image, a Keyhole Markup Language (KML) file that represented the randomly generated survey points produced for the 2019 images, was imported into Google Earth. Using the 2008 Google Earth photographic image, each imported point was photo interpreted and a class assigned.

i-Tree automatically calculates the standard error (SE) and 95% confidence intervals from the photo-interpreted classifications, as shown in the example in the Tables 10 and 11 below where 1000 sample points have been classified as either tree or non-tree within the City. For details of confidence level calculation refer to the USDA (2011) i-Tree Canopy Technical Notes.

Table 10. SE calculation

N = Total number of sampled points = 1000
n = Total number of points classified as trees = 330
p = n/N = (330/1000 = 0.33)
q = 1-p = (1-0.33 = 0.67)
SE = √ (pq/N) = √ (0.33 x 0.67/1000) = 0.0149

adapted from (USDA 2011)

Table 11. Estimate of SE **(N = 1000) with varying p**

P	SE
0.01	0.0031
0.1	0.0095
0.3	0.0145
0.5	0.0158
0.7	0.0145
0.9	0.0095
0.99	0.0031

3.2.6 Urban Forest Metrics Detection using LiDAR

The LiDAR point cloud data as .las files were extracted from the Minnesota Department of Natural Resources (MNDNR) .laz files using laszip.exe file (rapidlasso 2017). The LiDAR data was pre-processed and analyzed using LiDAR360 software (GreenValley International Ltd 2019).

3.2.6.1 Preprocessing LiDAR Data

A mosaic of .las files was created encompassing the St Peter 2017 boundary. The point cloud was assigned classes by MNDNR (Table 12).

Table 12. LiDAR point cloud classification table

Class ID	**Description**	**Class ID**	**Description**
1	Unclassified	**8**	Model Keypoints
2	Bare earth Ground	**9**	Water
4	Vegetation	**10**	Ignored Ground
6	Buildings/Structures	**14**	Bridges
7	Low Point		

To improve the quality of the data, LiDAR data preprocessing included the reclassification of the point cloud and removal of outliers. LiDAR360 utilizes a multitude of options to classify or reclassify points. Initial classification was done using the Classify by Machine Learning module. This consisted of using a small training sample that was manually corrected to classify/reclassify points; LiDAR360 then used the random forests machine learning method in conjunction with the training sample (GreenValley International Ltd 2019) to edit the whole dataset in batches. After multiple re-runs including different training samples and changing a variety of parameters, e.g., building parameters, although the entire point cloud was classified, after inspection, the dataset was of visibly worse quality than the initial MDNR dataset.

The following three LiDAR point classification processes ultimately proved successful in improving data quality. First, bare earth ground points were classified/reclassified using the improved progressive TIN densification filtering algorithm as detailed in Zhao et al. (2016); GreenValley International Ltd (2019). The only parameter change for the model run was to change the maximum building size from a default length of 65.66 ft to reflect the actual length of the largest building within the research area which was 524.93 ft. Once bare earth ground points were classified the next process was to use a concoid filter to refine the bare earth ground points.

> Ground points are classified by fitting quadratic surfaces. The specific idea is: first, mesh the point cloud, select the lowest point of the grid within a certain size window to construct the quadric surface, and compare the distance between the point cloud and the fitting surface in the calculation window and the set distance threshold, which is less than this. Thresholds are classified as ground points; otherwise, they are classified as non-ground points. (GreenValley International Ltd 2019)

Parameters were left at the default values. Finally, the point cloud was classified using the Interactive Editing module, paying particular attention to the vegetation points. This module allows the user to manually edit points or groups of points by using a profile tool including real-time changing TINs to examine and alter classification of the point cloud. The preprocessed LiDAR data was then visually compared to the 2008 NAIP photographic image within ArcGIS. In addition, normalization, the removal of topographic relief elevation effects, was done by subtracting the closest classified bare earth ground point elevation from other classified points' z value (GreenValley International Ltd 2019).

3.2.6.2 Urban Forest Canopy Height

To create a canopy height model (CHM), a Digital Surface Model (DSM) and a Digital Elevation Model (DEM) were created. For both, as the area is urban, a Spike Free TIN was used as the interpolation (Zhao et al. 2016; GreenValley International Ltd

2019). Vegetation returns were used in place of first returns to improve accuracy by removing buildings, etc., which in an urban environment can be equal to or higher than the urban canopy. The DSM was then subtracted from the DEM creating a CHM.

3.2.6.3 Urban Forest Canopy Density

Canopy cover density was determined by calculating the ratio of vegetation returns to the total number of LiDAR first returns for a pixel (Jennings, Brown, and Sheil 1999; Ma, Su, and Guo 2017; GreenValley International Ltd 2019). Vegetation below 6.6 ft. was removed and the pixel size was determined by measuring the width of the largest individual tree canopy: 108.27 ft.

3.2.6.4 Tree Metrics

Individual tree attributes, e.g., tree location, height, crown diameter, area and volume were determined using two different tree segmentation models: CHM segmentation and point cloud segmentation model.

In CHM segmentation, watershed segmentation is used to recognize and demarcate individual tree crowns. The watershed segmentation algorithm is based on the inversion of individual tree canopy points to represent a catchment basin. At the level of which the water would fill the catchment basin and start to overflow, that surface represents the bottom of the individual tree canopy (Chen et al. 2006; GreenValley International Ltd 2019). From this segmentation, tree location, height, crown diameter, and crown area are calculated. CHM segmentation was based on the CHM created to determine urban forest canopy height as detailed in 3.2.6.2.

Point cloud segmentation is based on using the relative spacing between trees. It uses the concept that spacing at the top of the trees is greater than at the bottom, so starting from the top and working down, LiDAR points are included and excluded based on their relative distance to each other. To mitigate the consequences of smaller relative spaces at the bottom of the tree, the points are ordered in sequence and removed based on a spacing threshold. Using this segmentation process, tree location, height, crown diameter, crown area, and volume are calculated (Li et al. 2012; GreenValley International Ltd 2019). For extraction of tree metrics, a normalized point cloud consisting of vegetation points was created and due to the close proximity of trees in areas within the research site, the spacing threshold was set to 1.64 ft.

4 Results and Discussion

4.1 Accuracy Assessment of OBIA and Stratified Random Sampling Results

4.1.1 Accuracy Assessment of OBIA

It is important to contextualize and assess the error associated with the extraction of the canopy cover. In general, for OBIA (Table 13), the overall classification accuracy is excellent: over 90% with the exception of 1995 (89.33%). The overall Kappa statistics show strong agreement (>0.8) (Congalton and Green 2019) between the years, with the exception of 1995 (0.78). A possible answer for the lower overall classification accuracy and overall kappa statistics for 1995 could be that the 1995 photographic image has relatively low spectral variability even though it was scanned at a high resolution. This may be due to the fact that the digitally scanned image is essentially a copy of the hardcopy photograph not the original negative and therefore may lose spectral information during the scanning process (Veteto 2019b). Each pixel value is a whole number not a floating number. Feature Analyst recommends not using a histogram stretch on scanned maps and when this was attempted this did not improve the classifications (Overwatch Systems Ltd 2015). Feature Analyst also recommends the use of Discrete band within the Input Bands Tab, rather than Reflectance (Overwatch Systems Ltd 2015). These two features utilized were the only major methodological differences from the other unscanned image methods.

Table 13. Overall canopy cover classification accuracy & overall kappa statistics

	Overall Classification Accuracy %	**Overall Kappa Statistics**
Year		
1938	94.00	0.87
1951	92.67	0.84
1964	94.67	0.89
1995	89.33	0.78
2008	96.00	0.92
2017 (1928)	90.67	0.81
2017 (2017)	94.67	0.89
2017 (Ground Truth)	92.67	0.82

In general, the error matrices for the entire period 1938-2017 (Table 14-21) show that the producer's accuracy (89-97%) of canopy cover and therefore the omission error ranges from 3% to 11%; this is slightly higher than user's accuracy (84-94%) and therefore a commission error of 16% to 6%. The exception is the 2017 OBIA (1928 boundary) (Table 19) where this phenomenon is reversed (86.76% producer's accuracy and 92.19% user's accuracy). However, different producers and user's accuracies were obtained when the 2017 St Peter City boundary was applied. This indicates accuracy assessment results are sensitive to the study site boundary.

Table 14. Error matrix for the 1938 forest canopy classification within the 1928 boundary

Year	Reference / Classified Land Cover	**Non-Canopy**	**Canopy**	Total	Users Accuracy
1938	**Non-Canopy**	87	2	89	-
	Canopy	7	54	61	88.52%
Total		94	56	150	
Producers accuracy		-	96.43%		

Table 15. Error matrix for the 1951 forest canopy classification within the 1928 boundary

Year	Reference / Classified Land Cover	**Non-Canopy**	**Canopy**	Total	Users Accuracy
1951	**Non-Canopy**	89	2	91	-
	Canopy	9	50	59	84.75%
Total		98	52	150	
Producers accuracy		-	96.15%		

Table 16. Error matrix for the 1964 forest canopy classification within the 1928 boundary

Year	Reference / Classified Land Cover	**Non-Canopy**	**Canopy**	Total	Users Accuracy
1964	**Non-Canopy**	87	2	89	-
	Canopy	6	55	61	90.16%
Total		93	57	150	
Producers accuracy		-	96.49%		

Table 17. Error matrix for the 1995 forest canopy classification within the 1928 boundary

Year	Reference / Classified Land Cover	**Non-Canopy**	**Canopy**	Total	Users Accuracy
1995	**Non-Canopy**	78	6	84	-
	Canopy	10	56	66	84.85%
Total		88	62	150	
Producers accuracy		-	90.32%		

Table 18. Error matrix for the 2008 forest canopy classification within the 1928 boundary

Year	Reference / Classified Land Cover	**Non-Canopy**	**Canopy**	Total	Users Accuracy
2008	**Non-Canopy**	78	2	80	-
	Canopy	4	66	70	94.29%
Total		82	68	150	
Producers accuracy		-	97.06%		

Table 19. Error matrix for the 2017 forest canopy classification within the 1928 boundary

Year	Reference / Classified Land Cover	**Non-Canopy**	**Canopy**	Total	Users Accuracy
2017	**Non-Canopy**	77	9	86	-
	Canopy	5	59	64	92.19%
Total		82	68	150	
Producers accuracy		-	86.76%		

Table 20. Error matrix for the 2017 forest canopy classification within the 2017 boundary

Year	Reference / Classified Land Cover	**Non-Canopy**	**Canopy**	Total	Users Accuracy
2017 (2017 Boundary)	**Non-Canopy**	83	4	87	-
	Canopy	4	59	63	93.65%
Total		87	63	150	
Producers accuracy		-	93.65%		

Table 21. Ground truth error matrix for the 2017 forest canopy classification within the 2017 boundary

Year	Reference / Classified Land Cover	**Non-Canopy**	**Canopy**	Total	Users Accuracy
2017 (Ground Truth)	**Non-Canopy**	95	5	100	95.00%
	Canopy	6	44	50	88.00%
Total		101	49	150	
Producers accuracy		96.06%	89.80%		

To enhance the OBIA accuracy assessment validation it was necessary to implement ground truthing. Due to only being able to access public property combined with local flooding, the area available to ground truth within the City of St Peter was approximately ¼ of the total 2017 boundary. Despite these restrictions, the error matrix is comparable to those used within photointerpretation (Table 21).

4.1.2 Accuracy Assessment of Stratified Random Sampling

i-Tree's stratified random sampling technique's accuracy assessment is based on standard error (SE). SE shows there is a 95% confidence interval for 2008 and 2019 canopy cover data (1928 boundary) of + or – 1.45% which equates to 31.75 % - 28.85 % canopy cover and 1.53% which equates to 38.33 % -35.27% canopy cover respectively. For the 2019 data (2017 boundary) it is + or – 1.46% which equates to 31.86% - 28.94% canopy cover (Table 22).

Table 22. Standard Error of the canopy change statistics based on stratified random sampling method

Year (Boundary)	**Canopy (A)**	**% Area**	**+/-SE**	**% Area +SE**	**% Area -SE**	**+SE (A)**	**-SE (A)**
2008 (1928)	704.74	30.3	1.45	31.75	28.85	738.47	671.02
2019 (1928)	855.92	36.8	1.53	38.33	35.27	891.51	820.34
2019 (2017)	1280.90	30.4	1.46	31.86	28.94	1342.42	1219.38

4.1.3 Accuracy Assessment Conclusion

Comparing the results for both canopy extraction methods, the results are within 5% of total canopy area. The difference in results may be partially attributed to a difference in photographic image quality and resolution, e.g., Google imagery compared to NAIP imagery (USDA 2011). Overall, the OBIA and stratified random sampling accuracy results indicate there is a high confidence that both analysis techniques have a high enough level of accuracy to compare the results.

4.2 Urban Forestry Canopy Change, the Impacts of the 1998 Tornado, and Tree Diseases

4.2.1 Trend of Urban Forestry Canopy Change

For the 1928 City of St Peter boundary, the OBIA total canopy analytical results (Figures 7-15) show a general trend of canopy increase from 1938 to 2017, with a minimum percent area in 1938 of 20.68% to a maximum of 35.53% in 2008. During this time period, the data shows only two occasions when the canopy cover decreased, this was from 1938 to 1951 (20.68% to 18.00%) a decrease of 2.68%, and from 2008 to 2017 (35.53% to 35.30%) a decrease of 0.23%. On both occasions, in the subsequent measuring time interval, the canopy cover increased by 2.01% (1938-1964) and 1.27% (2017-2019 (stratified random sampling)) respectively. It is likely, based on the very small percentages of cover change, that the change is within error margins associated with accuracy assessment for both OBIA and stratified random sampling. However, as will be discussed, it is also possible that these changes are due to land use change or tree diseases. For the 1928 boundary, total canopy area can be split into two specific time frames: pre 1995 and post 1995. Pre 1995, percent area ranges from 20.68 (1938) to 25.97% (1995); post 1995, percent area ranges from 35.53% (2008) to 35.30% (2017).

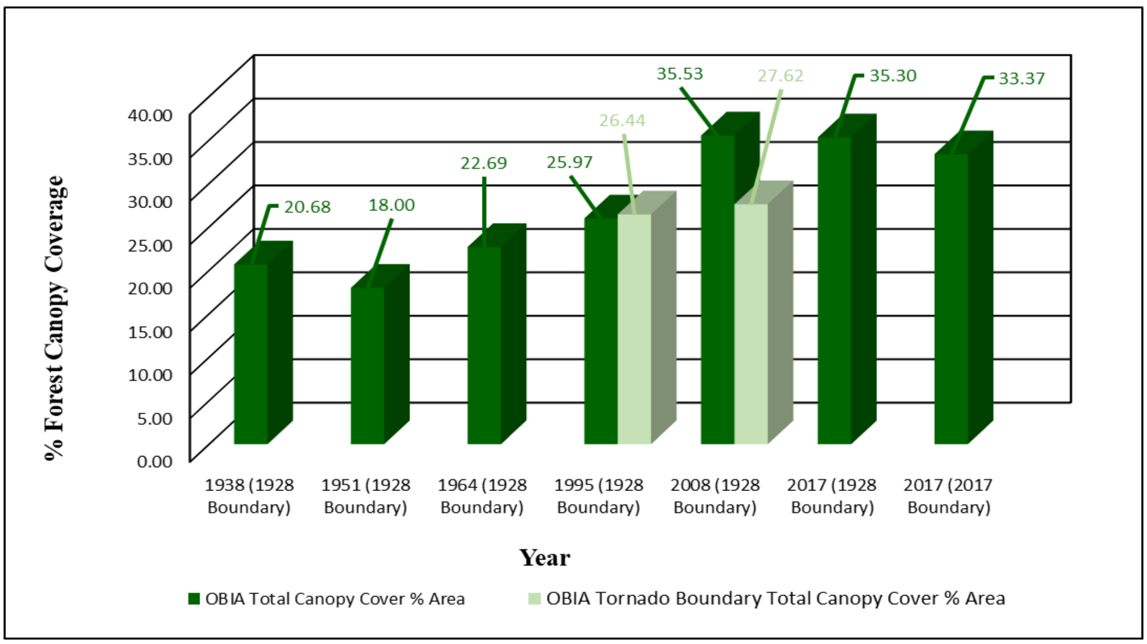

Figure 7. Graph of percent total forest canopy cover area from 1938 to 2017

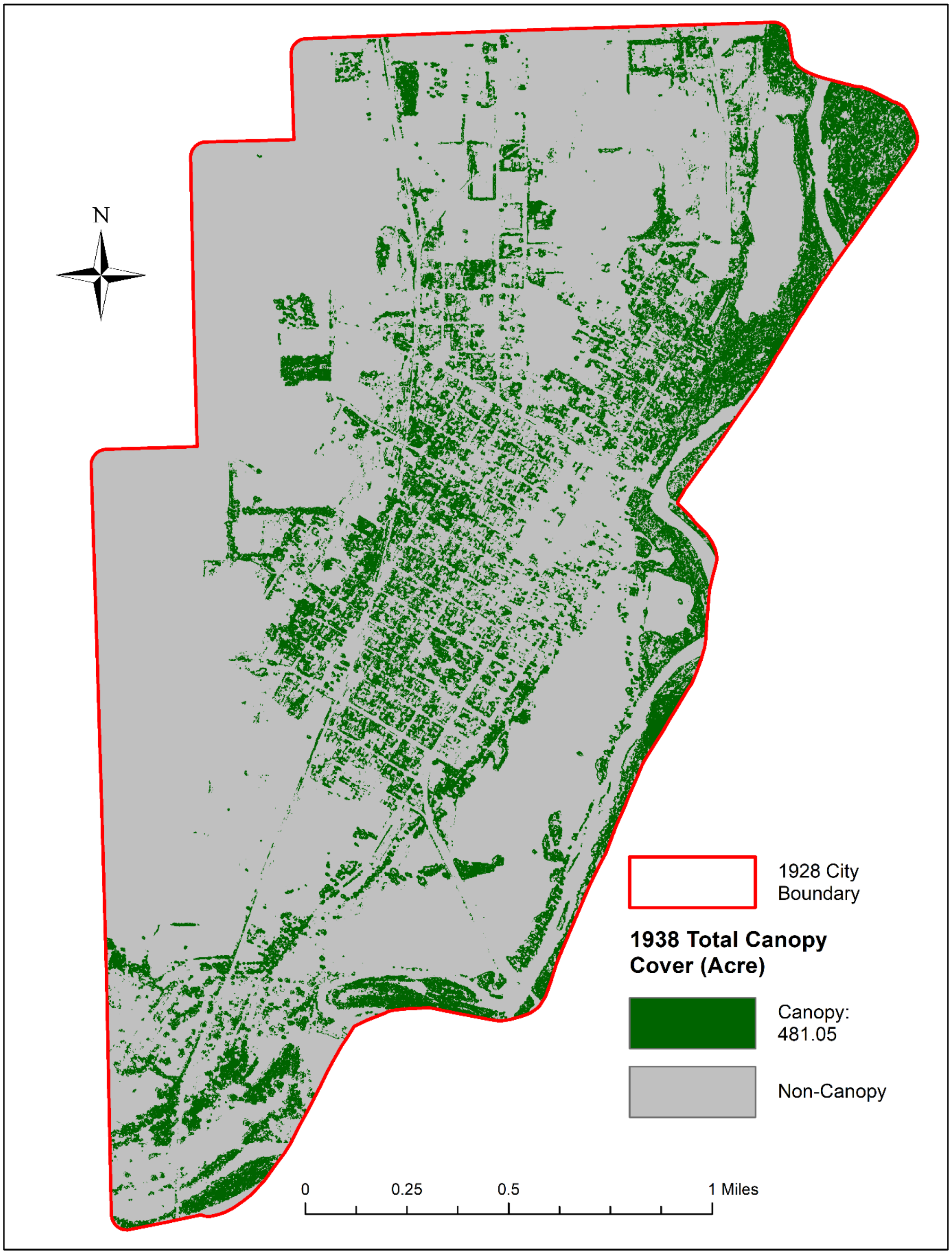

Figure 8. 1938 total canopy cover

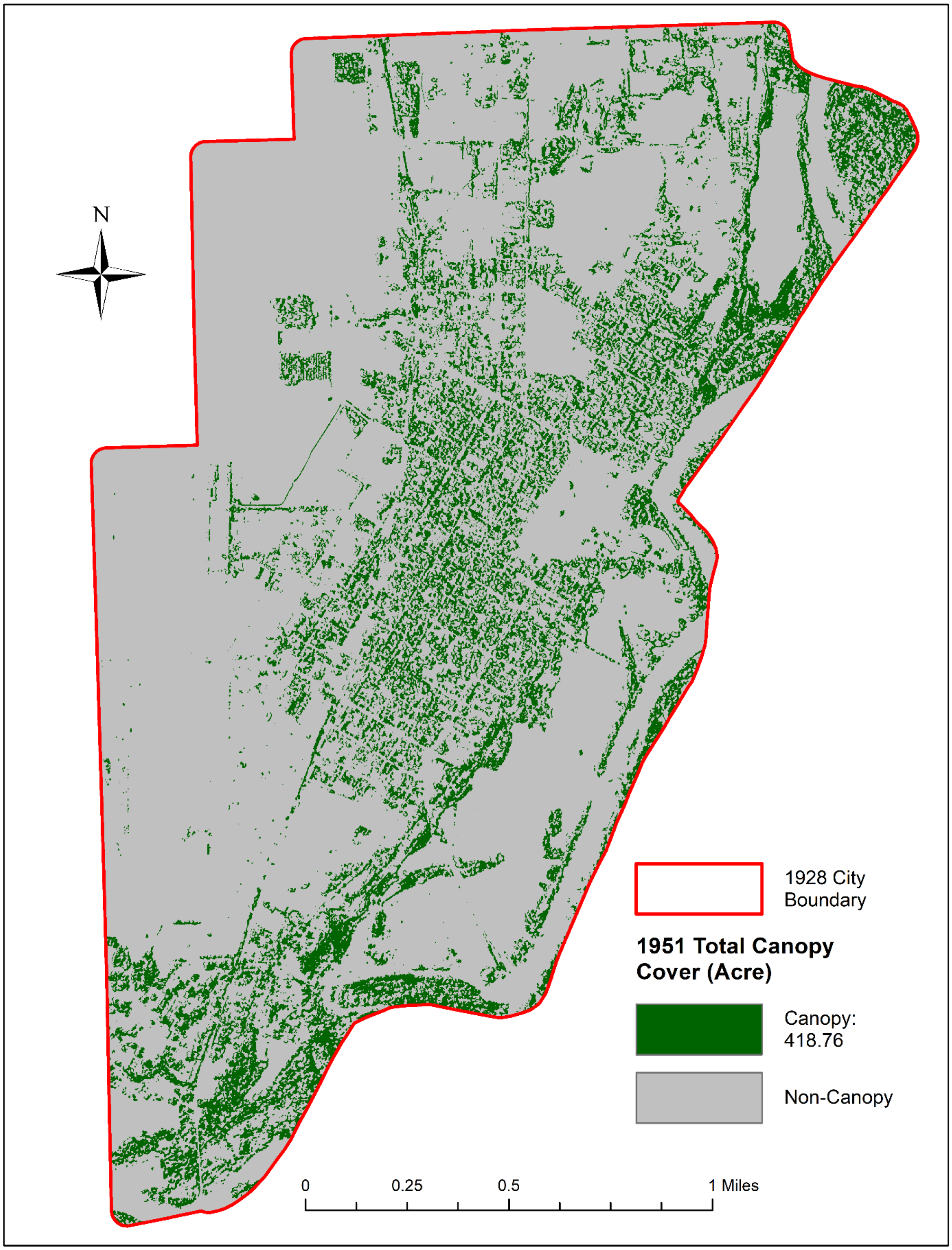

Figure 9. 1951 total canopy cover

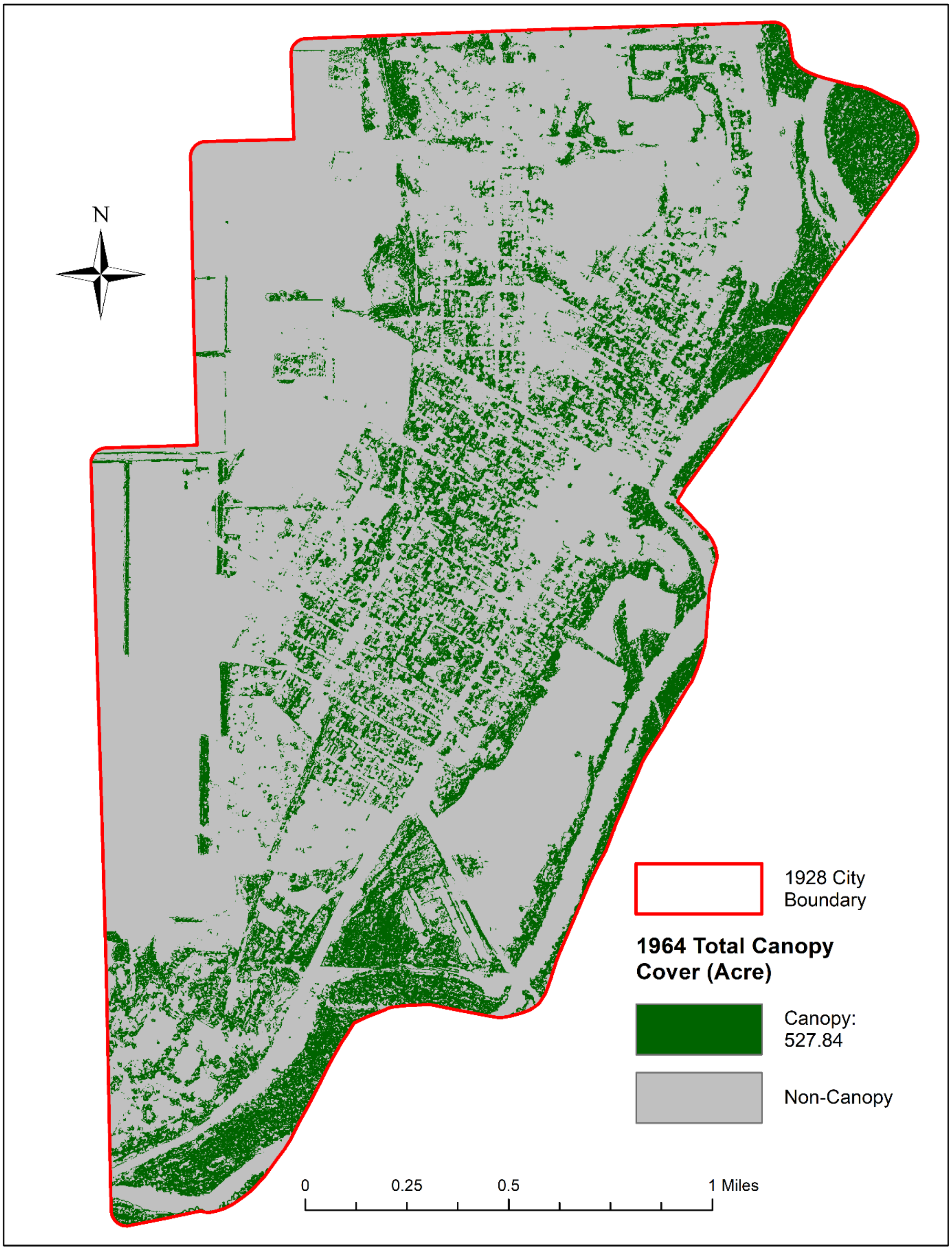

Figure 10. 1964 total canopy cover

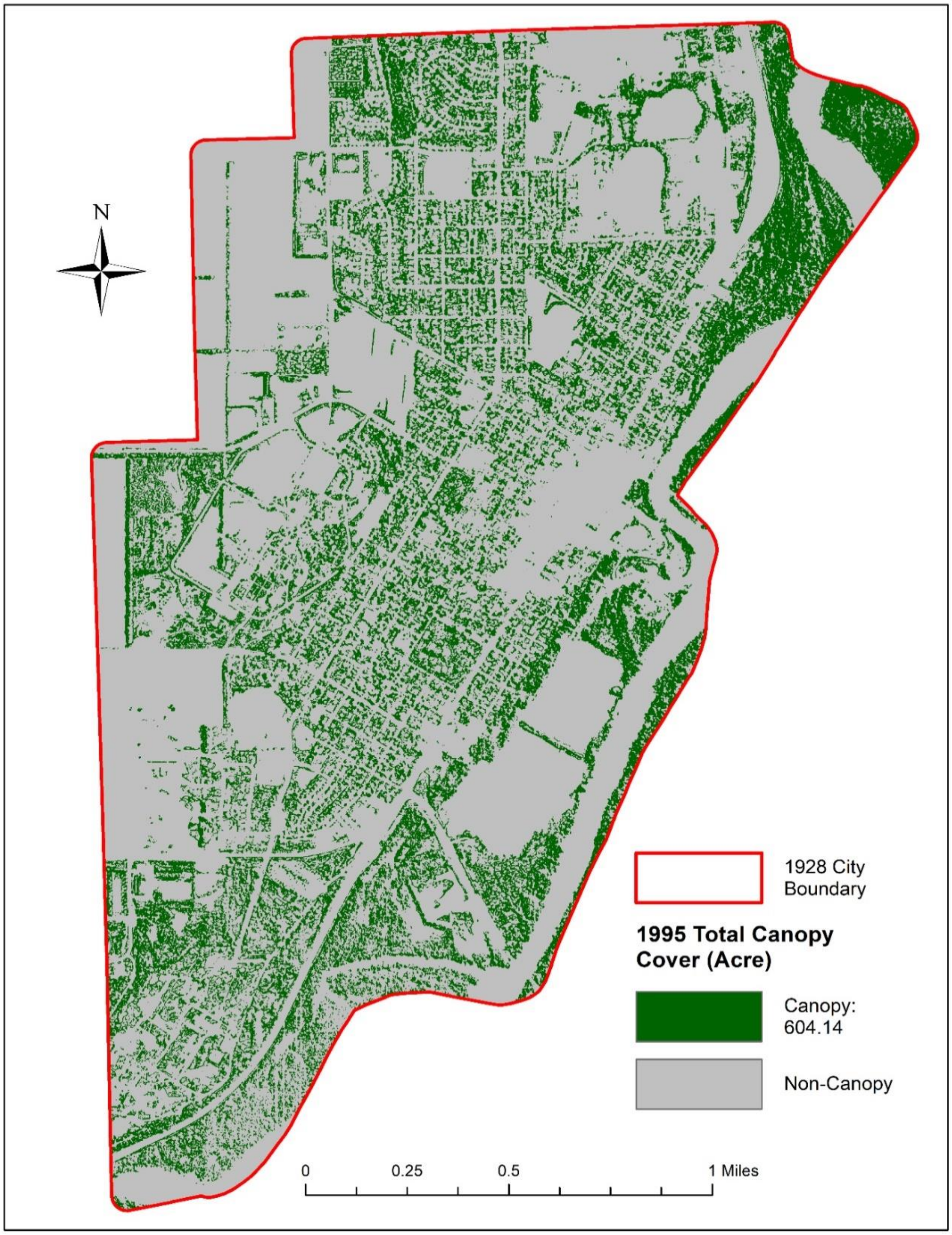

Figure 11. 1995 total canopy cover

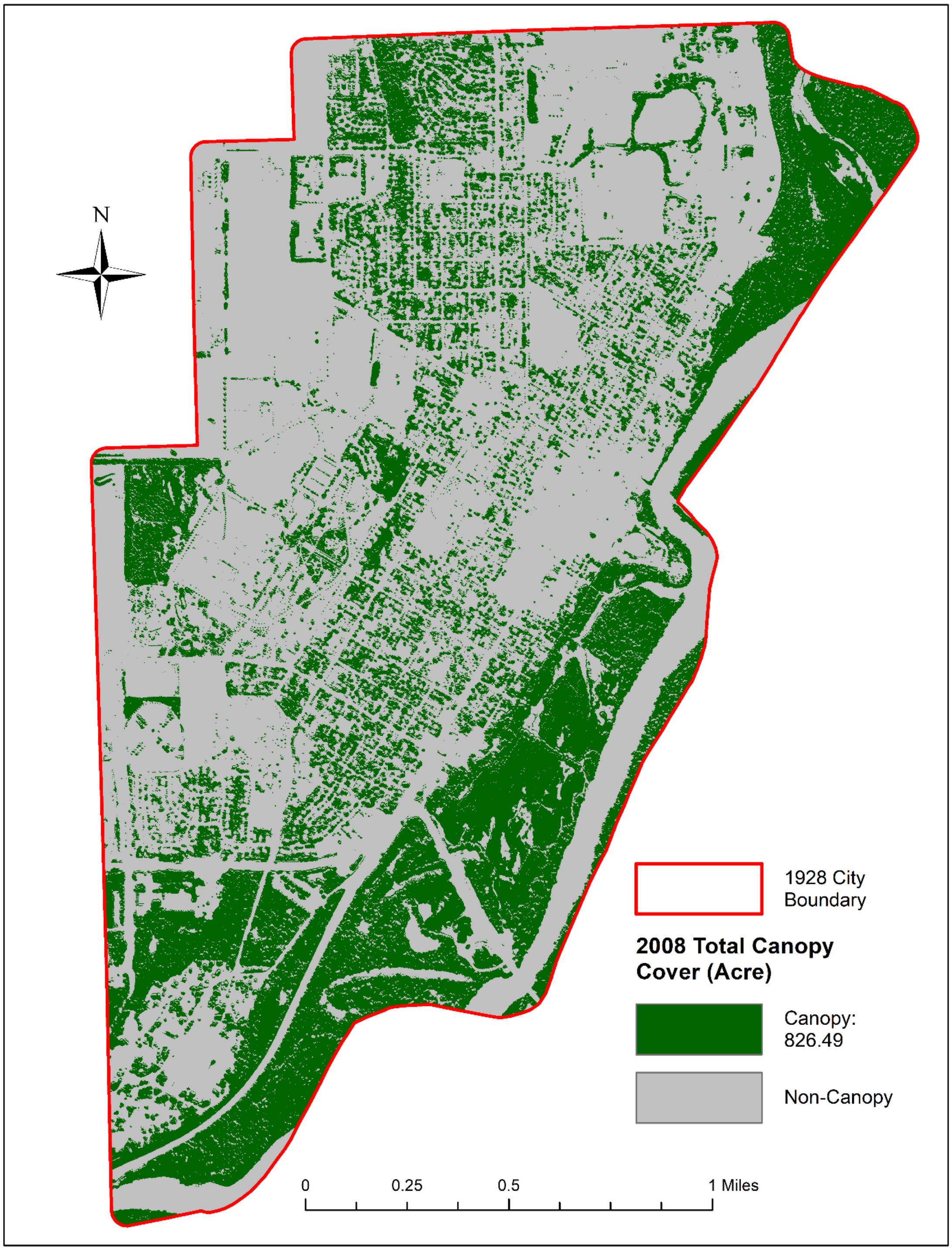

Figure 12. 2008 total canopy cover

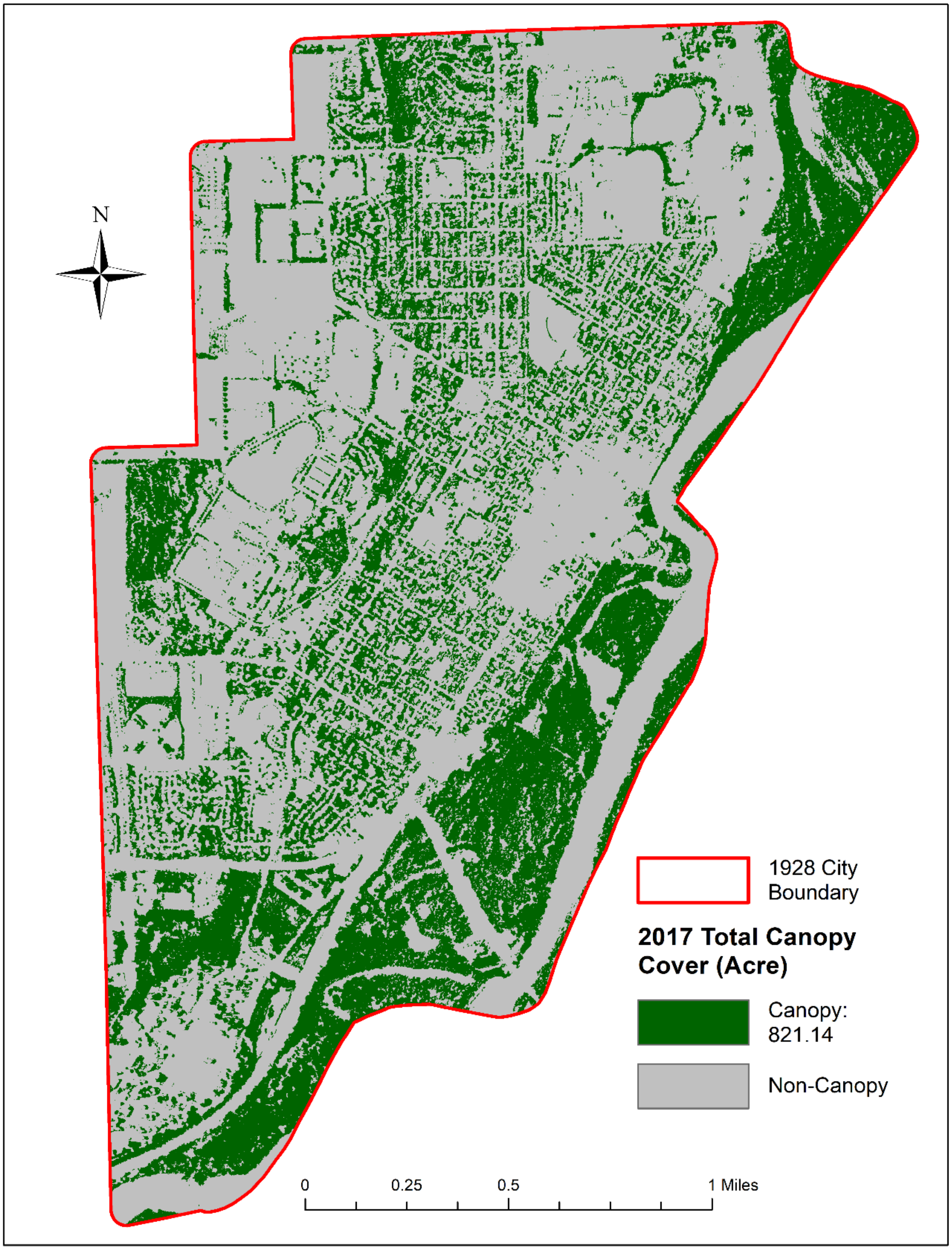

Figure 13. 2017 total canopy cover

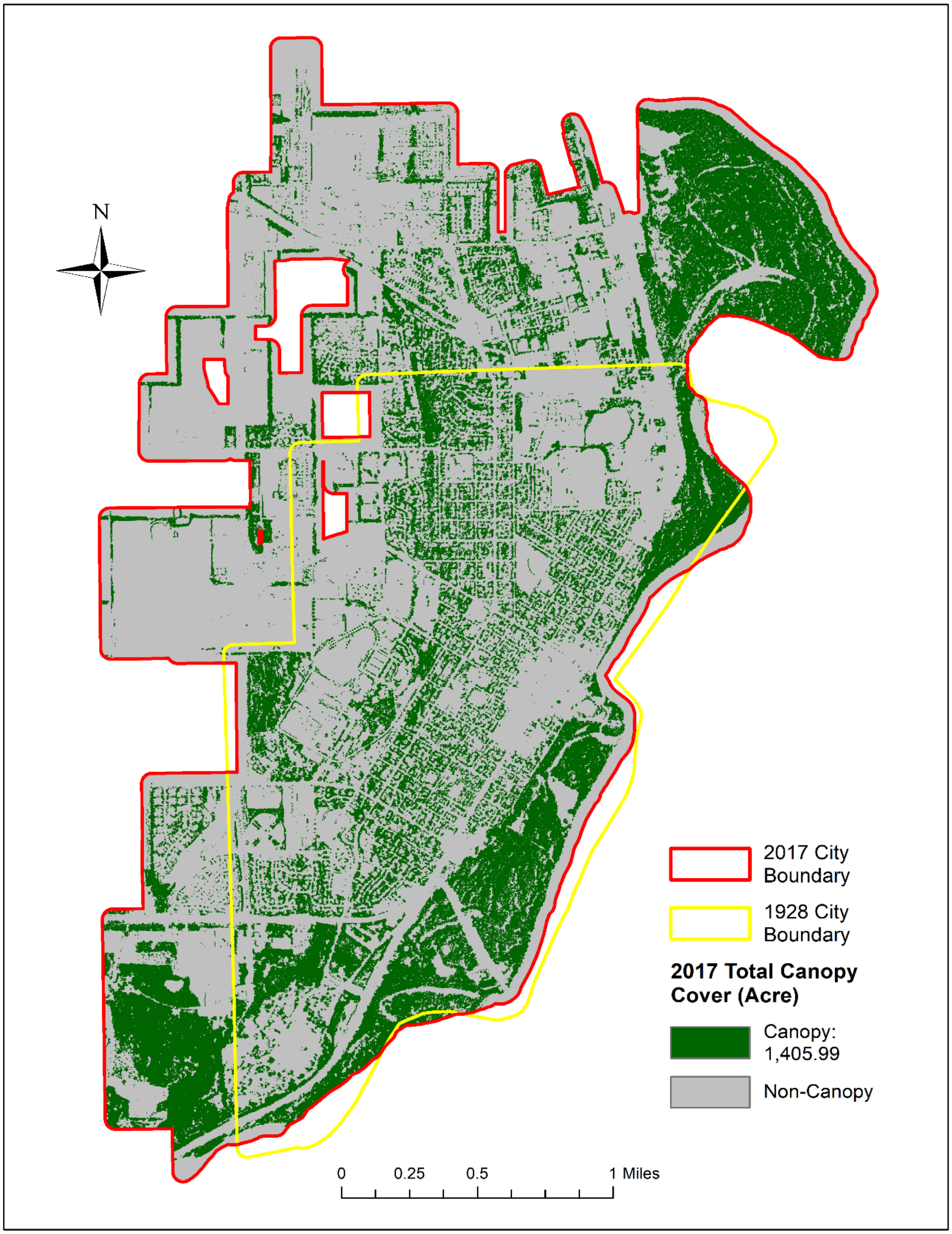

Figure 14. 2017 total canopy cover within the 2017 City boundary

Figure 15. 1995 & 2008 tornado tract total canopy cover

i-Tree's stratified random sampling confirms that from 2008 to 2019 the percentage canopy cover within the 1928 boundary is ~ 30 - 35% (Table 20 & Figure 16). From 1938 to 1995 (57 years), canopy cover increased as a proportion of overall City of St Peter area by 5%. From 1995 to 2017 (22 years), canopy cover increased by 10% of the total City of St Peter area. In fact, the 10% increase occurs between 1995 and 2008 and canopy cover remains stable from 2008 to 2019. The discussion of results has primarily focused on the 1928 City of St Peter boundary. However, it should also be noted; that regardless of the use of the 1928 or 2017 St Peter City boundary, the data shows that the areas have comparable canopy cover of ~34% from 2008 to 2017.

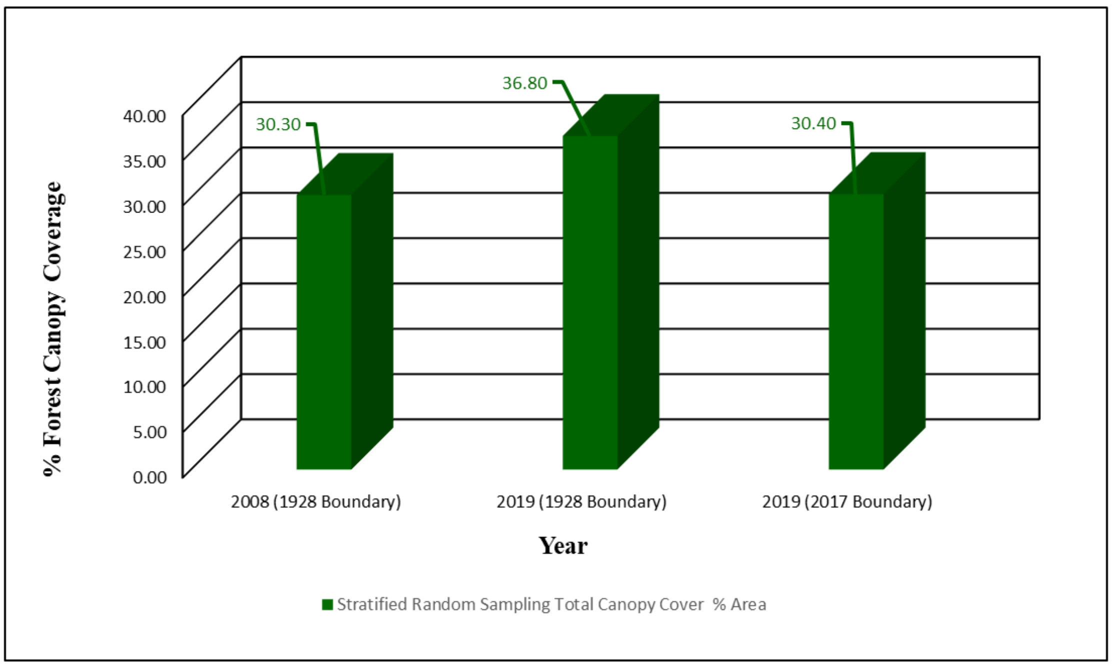

Figure 16. Graph of stratified random sampling total canopy cover percent area

With respect to canopy change detection, Table 23 details the changes between each time period. From 1938 to 1951, there is a small decrease in total canopy cover. The map (Figure 17) shows that the reduction in canopy cover is mainly along the Minnesota River. From 1951 to 1964, there is a ~4% increase in canopy, mainly along the Minnesota River flood plain and west boundary of the City of St Peter (Figure 18). From 1964 to 1995, there is a ~3% increase. Although, there is a reduction of canopy along the Minnesota River edge and flood plain, there is a marked increase in canopy cover along the west and north City of St Peter boundary (Figure 19). From 1995 to 2008, there is ~10% increase in canopy cover. This increase is spread throughout the City (Figure 20) and will be discussed in depth in the following section. From 2008 to 2017 (Figure 21), there is minimal 0.23% reduction in canopy cover, with canopy loss along the Minnesota River flood plain and an increase in cover throughout the City of St Peter city center. Overall, from 1938-2017 (Figure 22), the major increases in canopy cover are along the Minnesota River flood plain and the north and west boundaries of the City. It should be noted that only ~9% of total canopy area stays canopy from 1938 to 2017, predominantly within the City of St Peter city center and the north east Minnesota River flood plain. The increase in canopy area along the river flood plain is due to the change in land management; areas that were farmland are now naturalized areas of woodland. Canopy cover has also increased towards the edges of City of St Peter boundary, as new development has created new areas for planting trees from previous farmland.

It should also be noted that while there has been an overall increase in canopy cover, there are many areas that have remained non-canopy areas, or have changed from canopy to non-canopy, primarily before 1995. The change from canopy to non-canopy is particularly evident along the Minnesota River flood plain between 1938 and 1951 (Figure 17) and 1964 and 1995 (Figure 19), where the change in the river's position and the subsequent flooding have changed the land use. Within the St Peter City center area, Figures 17-19 also show areas that have changed from canopy to non-canopy; this is likely due to redevelopment, e.g., the division of a large parcel containing one property and trees into smaller parcels containing less trees. Finally, the non-canopy areas that have remained non-canopy are primarily along the outer edges of the City of St Peter (Figures 17-19); these areas continued to be primarily agricultural fields.

Table 23. OBIA canopy change detection

Canopy Change Years	**Canopy to Canopy (A)**	**% Area**	**Canopy to Non Canopy (A)**	**% Area**	**Non Canopy to Canopy (A)**	**% Area**	**Non Canopy to Non Canopy (A)**	**% Area**	**Sum of all (A)**
1938-1951	195.55	8.41	285.41	12.27	223.22	9.60	1621.35	69.72	2325.53
1951-1964	203.93	8.77	214.61	9.23	323.84	13.93	1583.09	68.08	2325.46
1964-1995	225.03	9.68	302.66	13.02	378.75	16.29	1418.95	61.02	2325.38
1995-2008	369.99	15.91	234.07	10.07	456.39	19.63	1264.99	54.40	2325.44
2008-2017	610.08	26.23	216.41	9.30	211.07	9.07	1288.32	55.39	2325.87
1938-2017	215.14	9.25	265.79	11.43	605.88	26.05	1238.63	53.26	2325.44
1938-1995	175.59	7.55	305.45	13.13	428.55	18.43	1416.28	60.89	2325.87
1995-2017	359.75	15.47	244.31	10.51	461.27	19.84	1260.11	54.19	2325.43
1995-2008 Tornado	203.12	14.58	165.25	11.86	181.59	13.04	843.15	60.52	1393.11

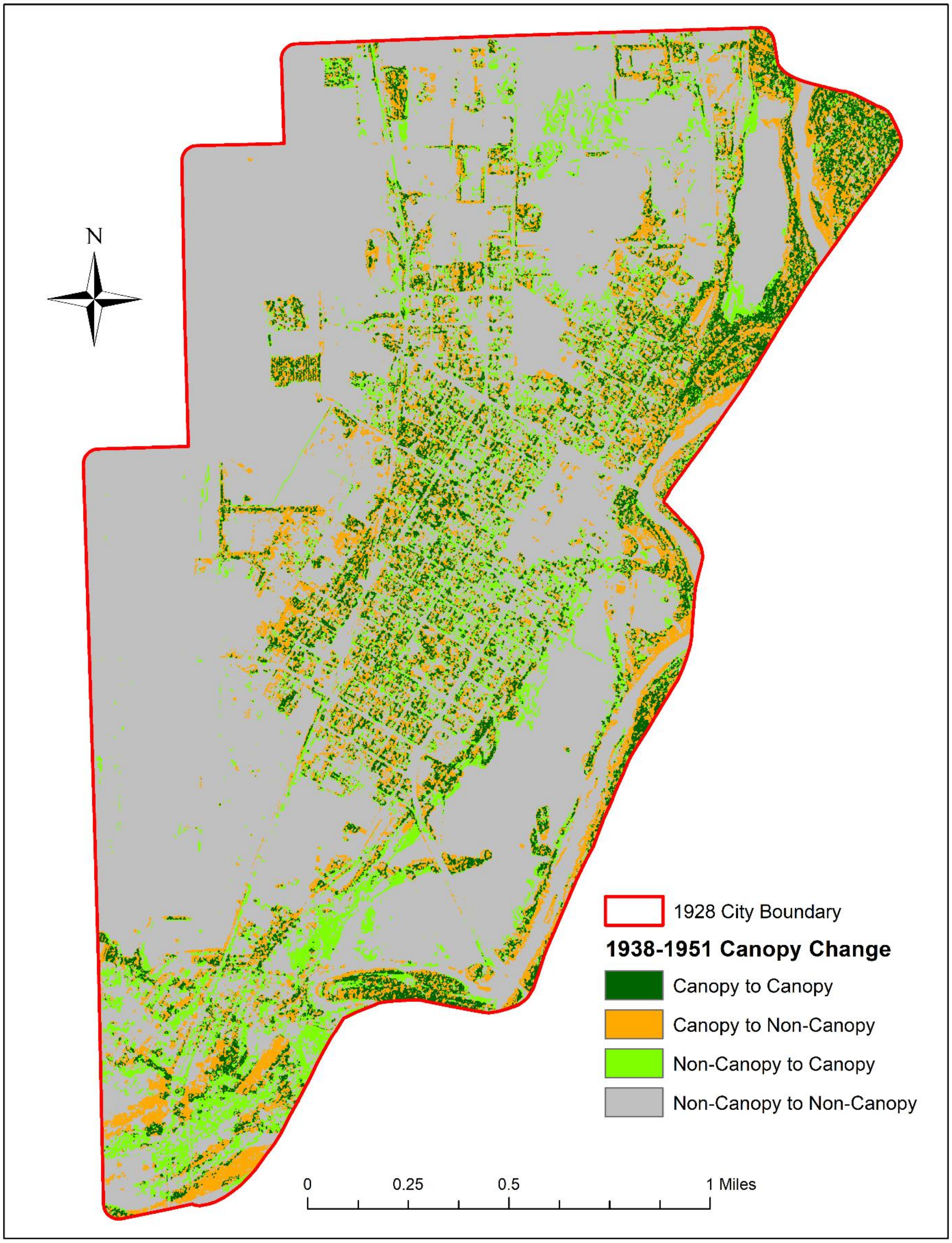

Figure 17. 1938-1951 canopy cover change

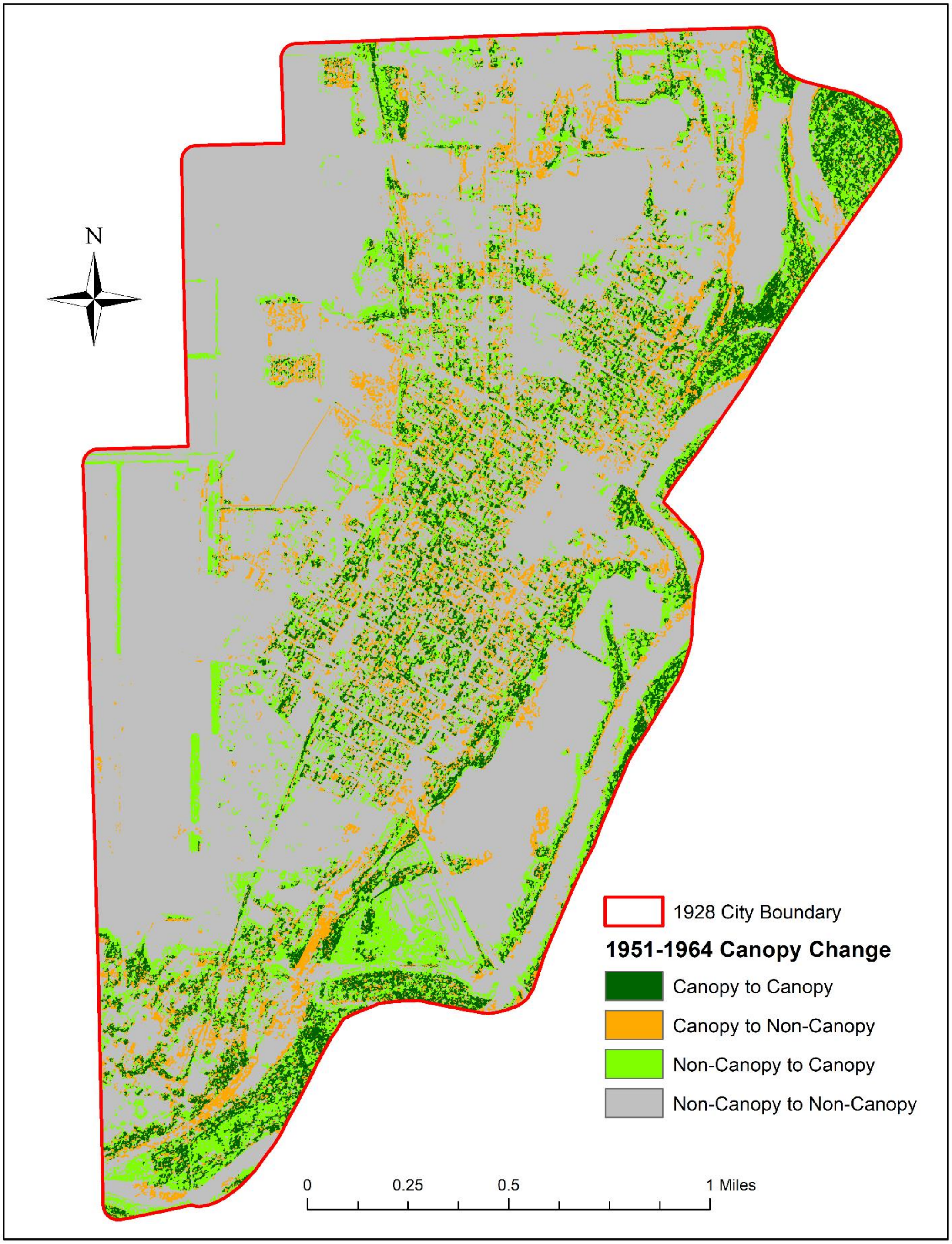

Figure 18. 1951-1964 canopy cover change

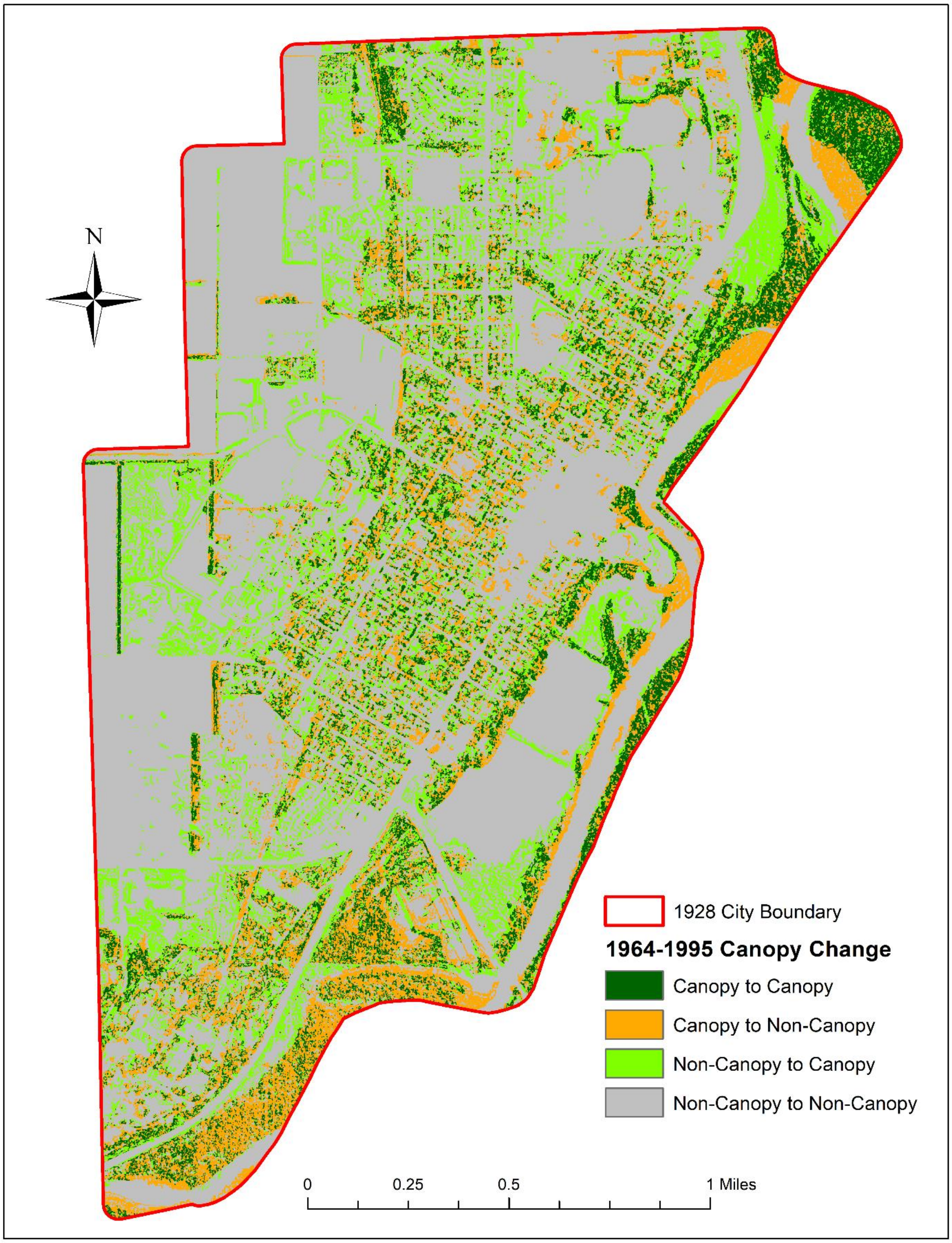

Figure 19. 1964-1995 canopy cover change

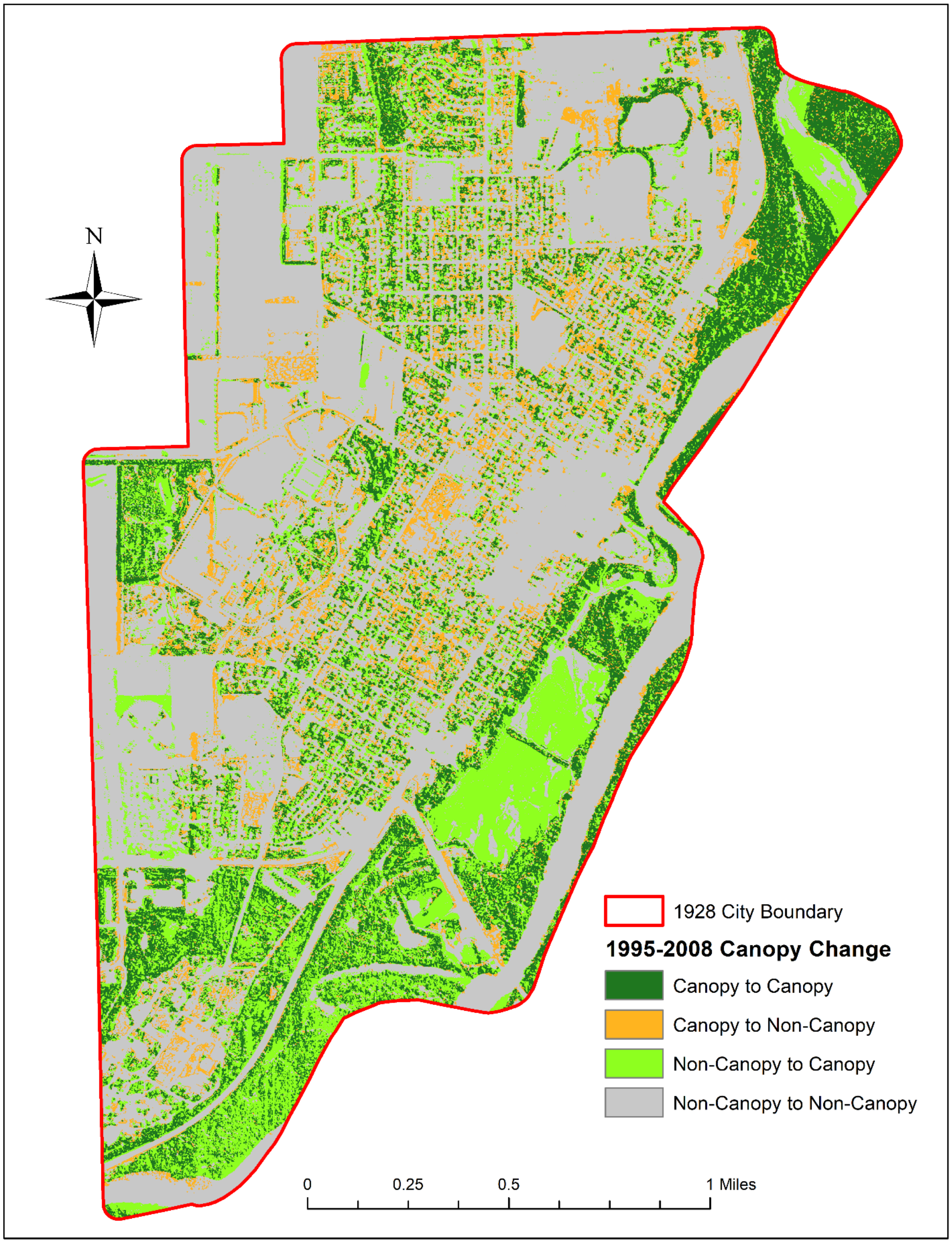

Figure 20. 1995-2008 canopy cover change

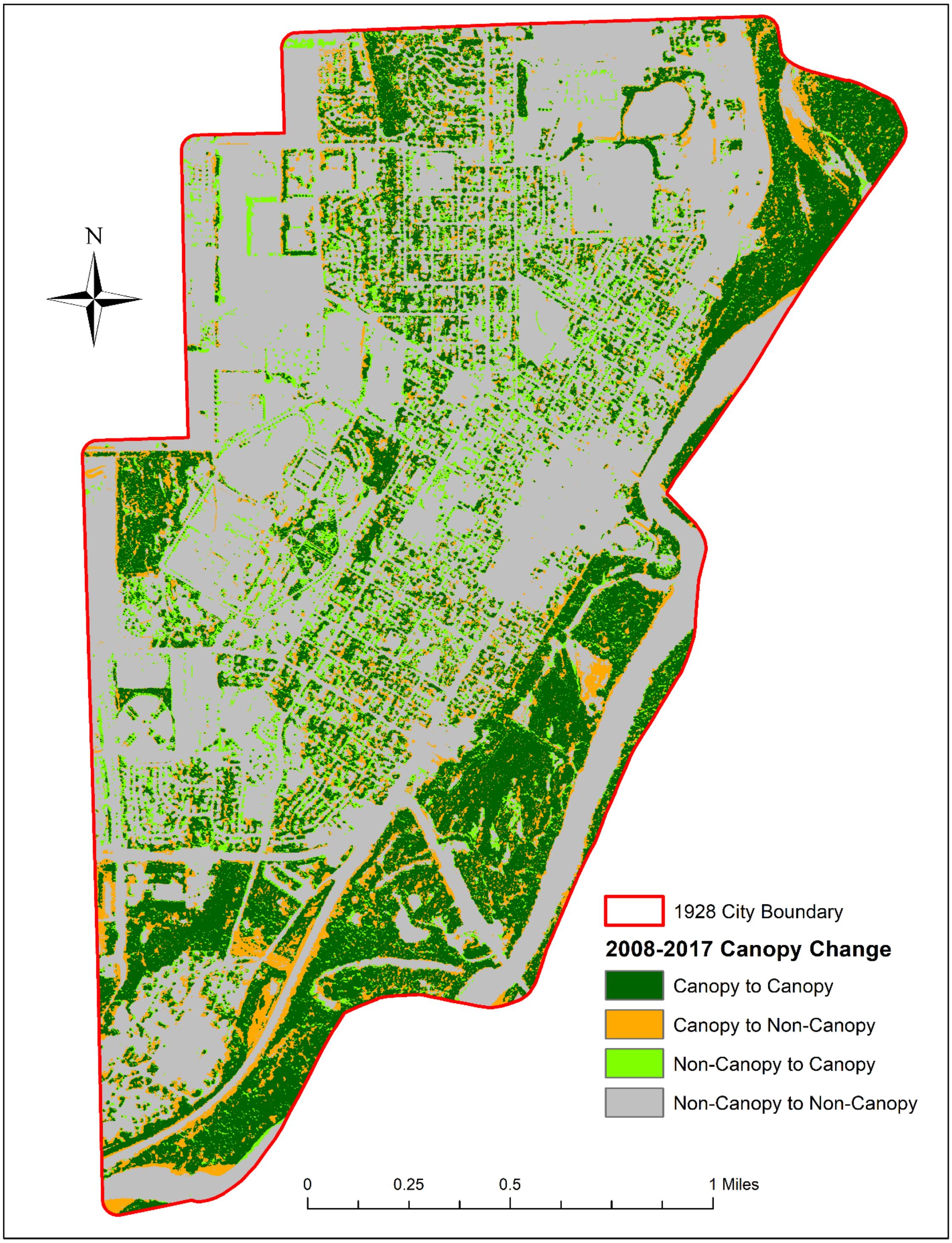

Figure 21. 2008-2017 canopy cover change

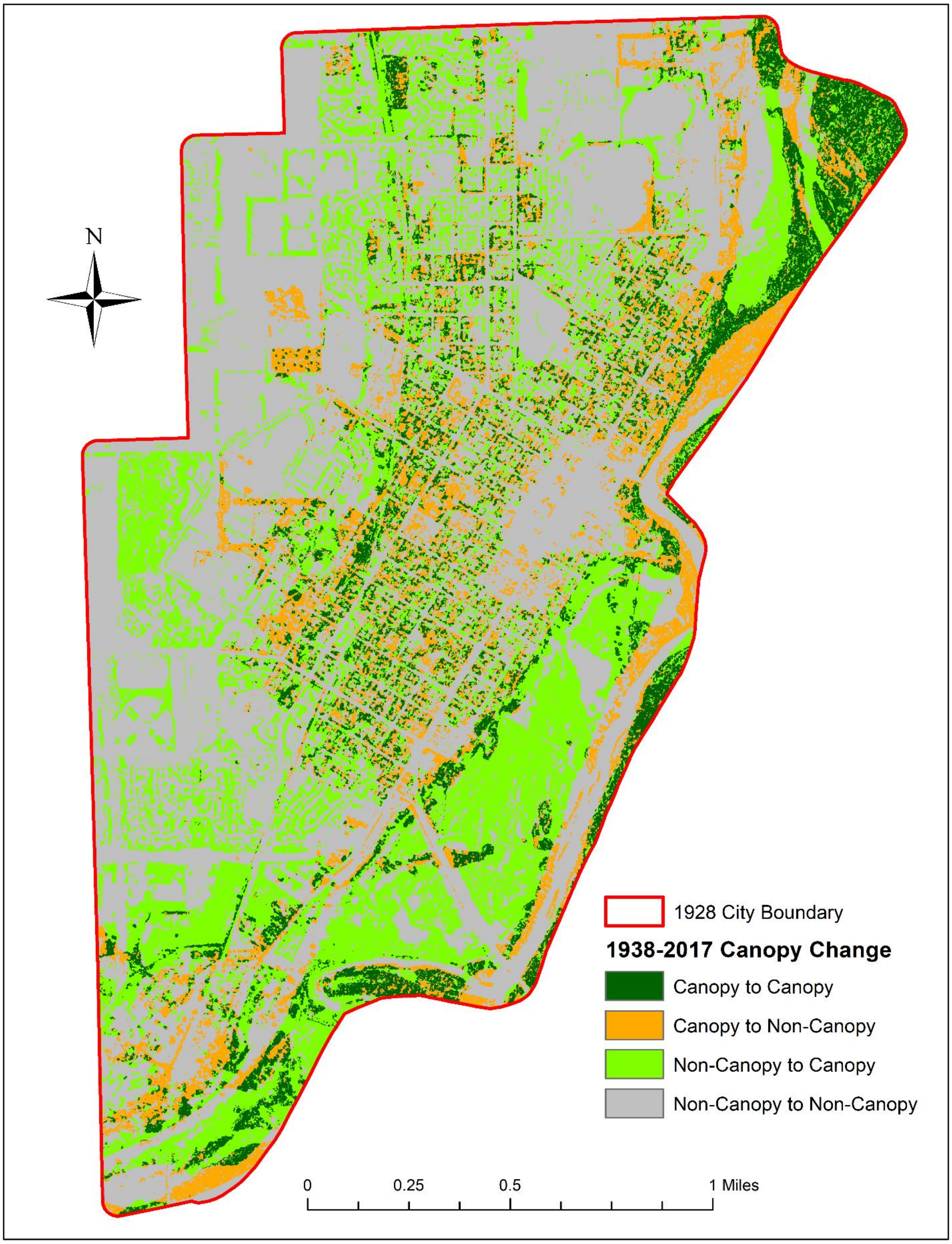

Figure 22. 1938-2017 canopy cover change

4.2.2 The Impacts of the 1998 Tornado

On 29 March 1998 at 5:18pm, an F3 tornado (158-206mph) swept through the City of St Peter, southwest to northeast, with a width of 2200 yds. (Figure 23) (NOAA 2017). The tornado caused considerable damage to both grey and green infrastructure (Figure 24).

The results of this study show that, at a minimum, 45% of the canopy cover within the tornado tract area was lost (Figure 7 & Table 21). After the tornado, the City of St Peter implemented a tree replanting program for replanting trees both on City of St Peter property, i.e., boulevards, parks, etc., and also allowing the public to buy trees to plant on private property. Forty percent of the replanting occurred within the tornado tract, with 60% planted in the remaining areas of St Peter. Overall, this led to the 10% increase in canopy cover by 2008; subsequently the canopy cover area has remained stable at ~35% through 2019 (Figures 7, 16 & 23, Table 21). The canopy change between 1995 and 2008 within the tornado tract (Figure 23) shows an increase in canopy cover on streets and backyards, as well as along the Minnesota River flood plain. The canopy to non-canopy area change is primarily due to the tornado, as these areas have changed due to infrastructure conversion or redevelopment, e.g., houses, parking lots, or newly created parks with no canopy cover established.

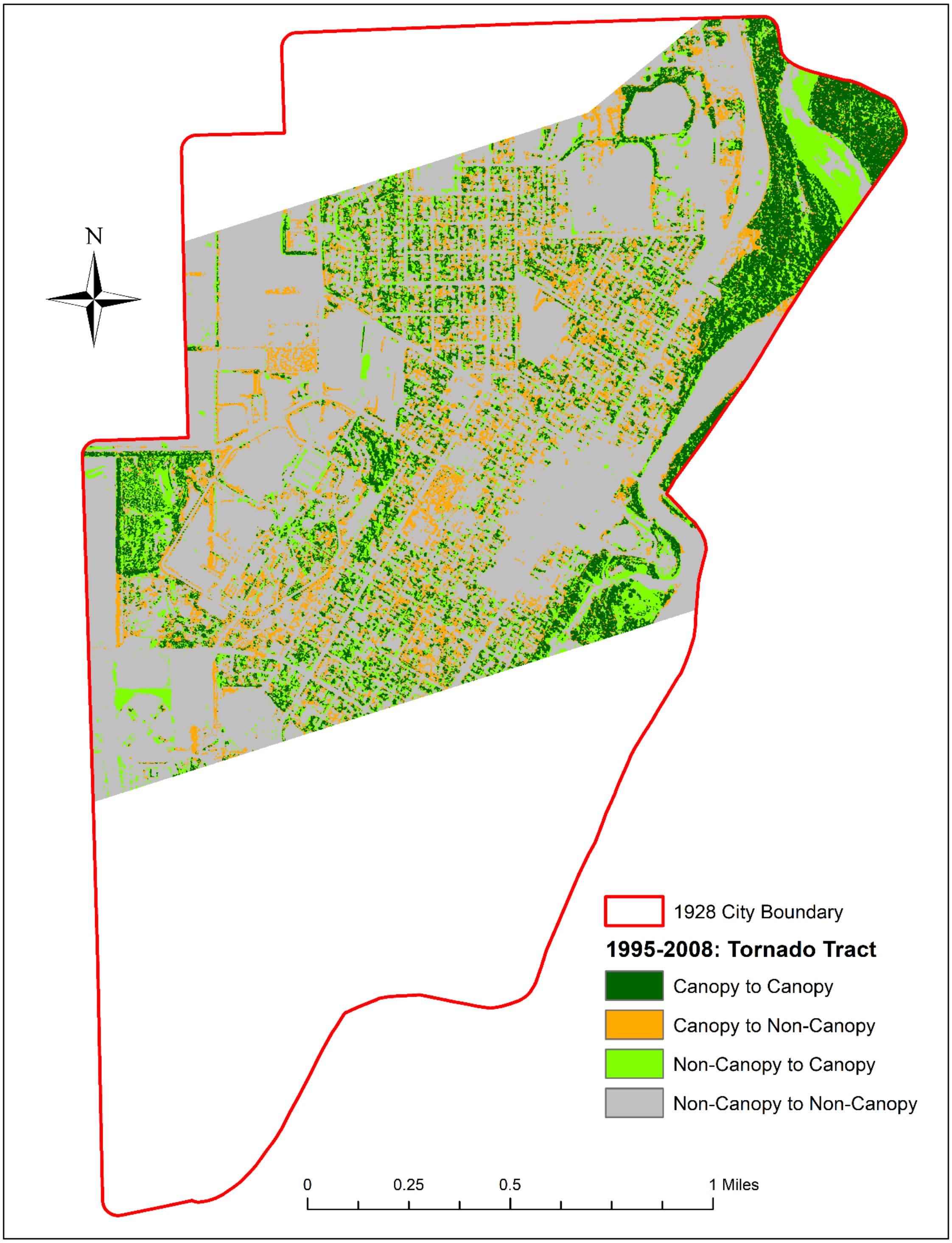

Figure 23. 1995-2008 tornado tract canopy change

Figure 24. Photographic image of 1998 tornado in City St Peter *http://www.saintpetermn.gov/sites/default/files/hotsheets/ HOTSHEETapril192017.pdf (last accessed 19 March 2017)*

4.2.3 Impacts of Tree Diseases

The butternut (*Juglans cinerea L.*) and particularly the American elm (*ulmus americana L*) trees were both highly visible within the urban forest and naturalized areas prior to the 1980s. However, due to DED (*Ophiostoma ulmi* and *o. nova-ulmi*) and butternut canker *Sirococccus clavigigenti-juglandacearum*) they have, with the exception of a few disease resistant "survivor" trees, disappeared from the landscape. Due to a probable combination of the resolution of the photographic images and the length of time between these images it was not possible to determine any meaningful correlation between the loss of these tree species and canopy cover. However, up until 1995 canopy cover stayed relatively constant, therefore replanting using other tree species, e.g., ash (*Fraxinus spp*.), maple (*Acer spp*.), or natural regrowth made up for the loss.

4.3 LiDAR Determined Urban Forest Height Assessment, Canopy Cover Density, and Tree Metrics

LiDAR was used to create a CHM, canopy cover density model and determine specific tree metrics for 2010.

4.3.1 Urban Forest Height Assessment

Figure 25 presents canopy cover height in 2010. The majority of the highest canopy and tallest trees are located in the naturalized areas within the Minnesota River flood plain (>50.00 ft). This would be expected due to the environmental conditions, e.g., soil, nutrients, water allocation, etc., allowing for extended growth of pioneer species specific to that environment such as Poplar (e.g., *Populus* deltoides) (MNDNR 2019b). The LiDAR canopy height data also shows the continued impact of the tornado of 1998 by showing the path of the tornado through the City of St Peter (Figure 20), as a function of the lack of height of canopy within the tornado tract (<25.00 ft) compared to the canopy height north and south (>50.00 ft) of the tornado boundary. The isolated areas of high canopy within the City center are trees that survived the tornado. The high canopy located on the east boundary in the flood plain area is unexpected based on the tornado path and the short time interval since the tornado. However, this is likely explained by the trees being protected from wind exposure due to the density of trees compared to more isolated individual trees within the urban environment, e.g., street, park, etc., and also the unpredictable nature of wind damage associated with tornados.

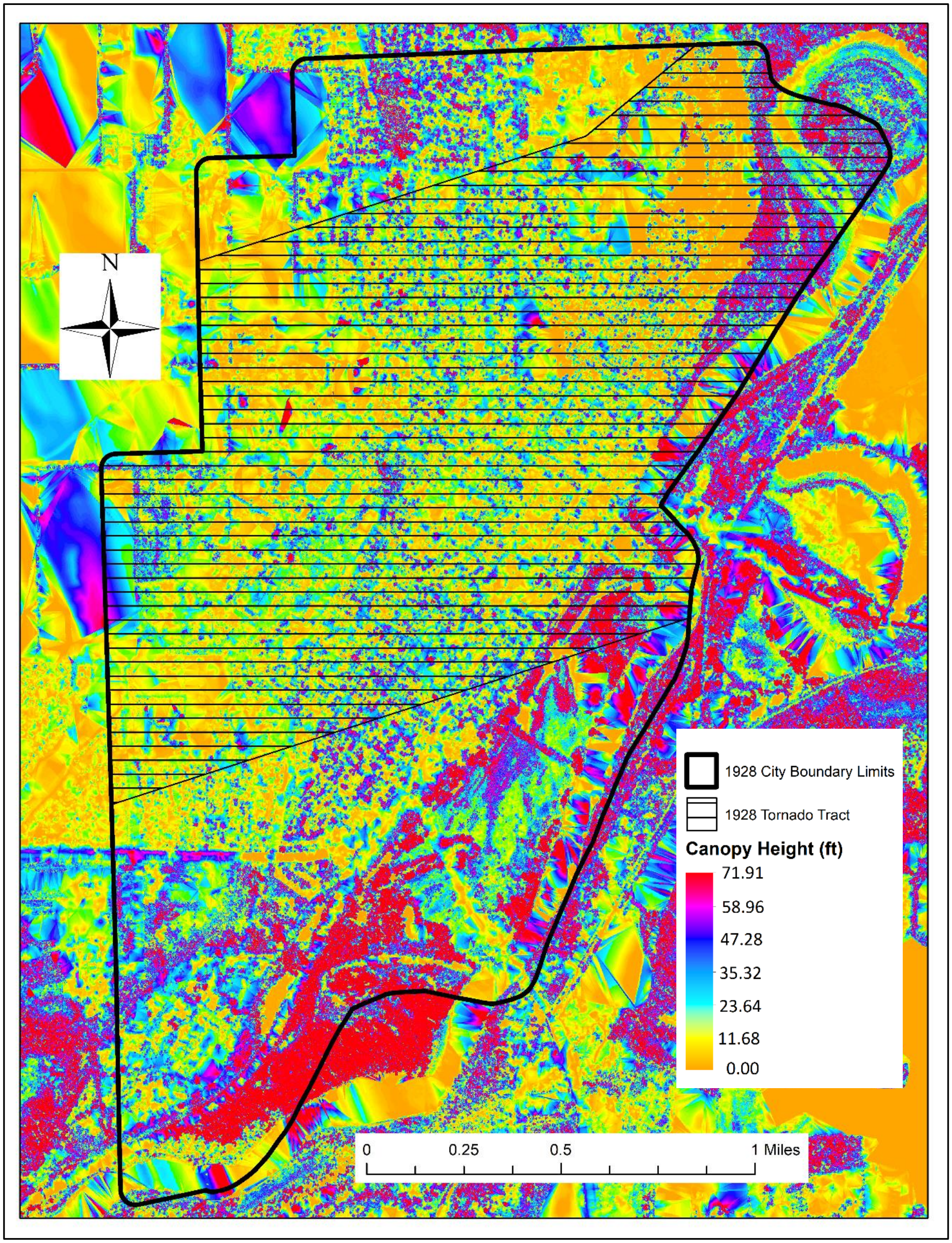

Figure 25. LiDAR canopy height model

4.3.2 Urban Forest Canopy Cover Density

The canopy cover density model (Figure 26) shows the total canopy coverage within a pixel area of 108.27 ft^2. Even though the resolution of canopy coverage (108.27 ft^2) is low compared to the OBIA 2008 data (3.06 ft^2) as the 2010 LiDAR data was

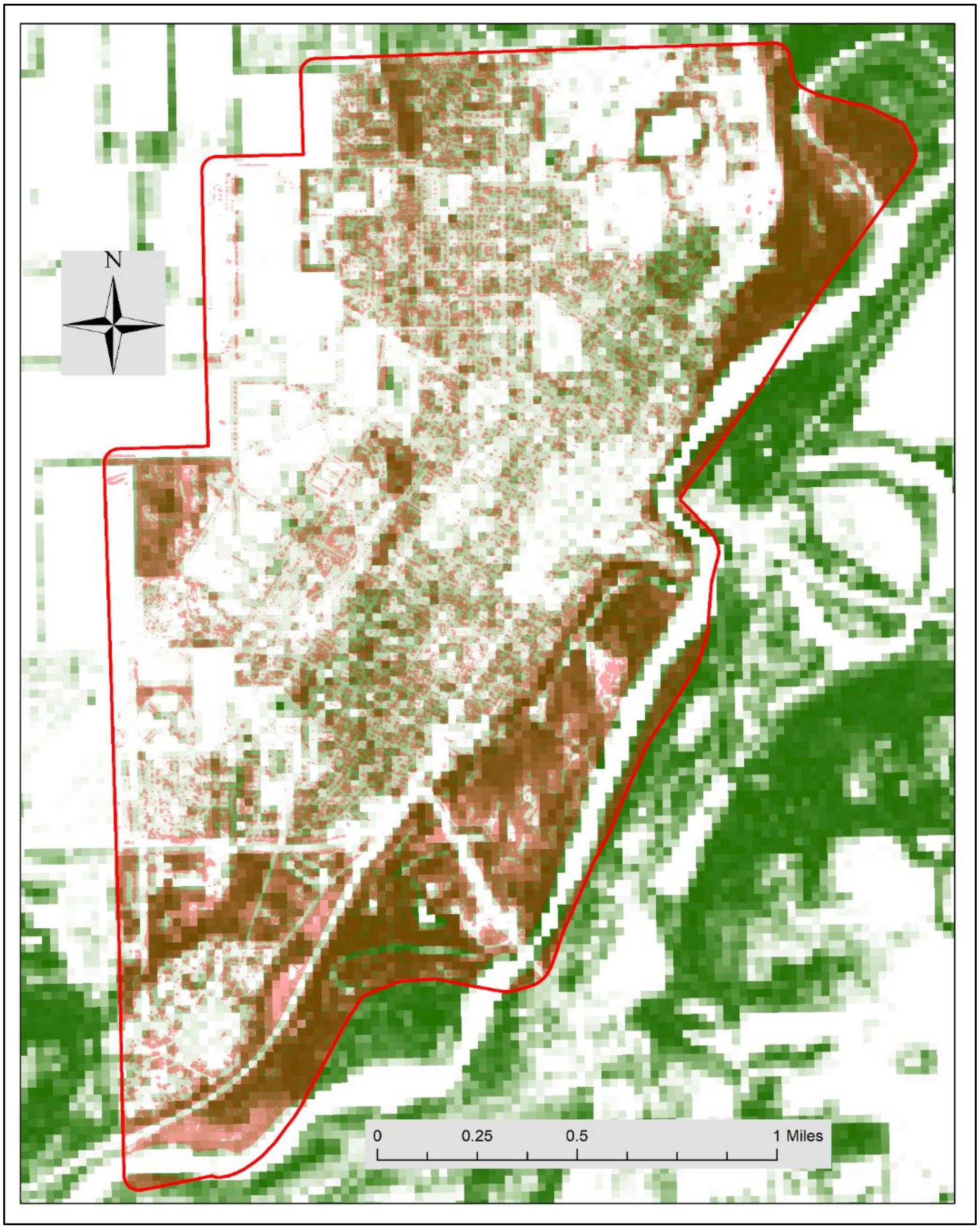

Figure 26. LiDAR canopy density

collected during leaf-off seasons, it is still possible to see how the 2010 LiDAR data corroborates the 2008 OBIA data and shows, as does the stratified random sampling data, that the OBIA data is of excellent quality.

4.3.3 Tree Metrics

Two separate methods (Canopy Height Model and point cloud) were used to determine individual tree attributes using LiDAR data. The tree attributes determined for both processes were tree location, tree height, crown diameter, and crown area. The point cloud segmentation process also provided crown volume (Table 24). However, both processes did not extract the same number of trees; for example, three trees were not extracted using the point cloud algorithm. Table 24 shows an example selection of tree attributes for trees located along the south west corner of Minnesota Square Park (Figure 27). Both the x, y tree locations are within reasonable parameters of accuracy for my research. However, the remaining metrics each have accuracy discrepancies and cannot be rectified without performing regression analysis, which is not included within this study. Tree height for both processes based on visual assessment are within the reasonable parameters, however between processes tree heights vary by 3-8 ft. For crown diameter and crown area the differences are even greater between processes, e.g., for the same tree, CHM crown diameter 84.52 ft vs. point cloud crown diameter 127.88 ft.. The same tree had a CHM crown area of 5611 ft^2 vs. point cloud crown area of 12,844.83 ft^2.

Table 24. LiDAR tree attributes from sample area using the canopy height model (CHM) and Point cloud (PC) methods

	Tree ID	Tree Location X	Tree Location Y	Tree Height (ft)	Crown Diameter (ft)	Crown Area (ft^2)	Crown Volume (ft^3)
CHM	212174	423011.80	4907701.84	41.33	84.52	5611.01	N/A
PC	26684	423013.49	4907699.86	47.36	127.88	12844.83	204471.98
CHM	212242	423019.00	4907693.44	37.59	62.67	3084.51	N/A
PC	26706	423023.39	4907692.63	43.91	39.73	1239.61	20188.21
CHM	212267	423027.40	4907689.84	40.70	42.84	1441.50	N/A
PC	26670	423029.57	4907687.71	48.83	48.59	1854.50	30006.84
CHM	212285	423033.40	4907687.44	40.82	38.47	1162.50	N/A
PC	26695	423040.18	4907683.88	44.88	103.54	8419.32	165345.25
CHM	212299	423029.80	4907685.04	38.42	29.80	697.50	N/A
PC	No Value	No Value	No Value	No Value	No Value	No Value	No Value
CHM	212324	423037.00	4907682.64	39.29	62.82	3100.01	N/A
PC	No Value	No Value	No Value	No Value	No Value	No Value	No Value
CHM	212355	423049.00	4907680.24	28.29	37.96	1131.50	N/A
PC	No Value	No Value	No Value	No Value	No Value	No Value	No Value

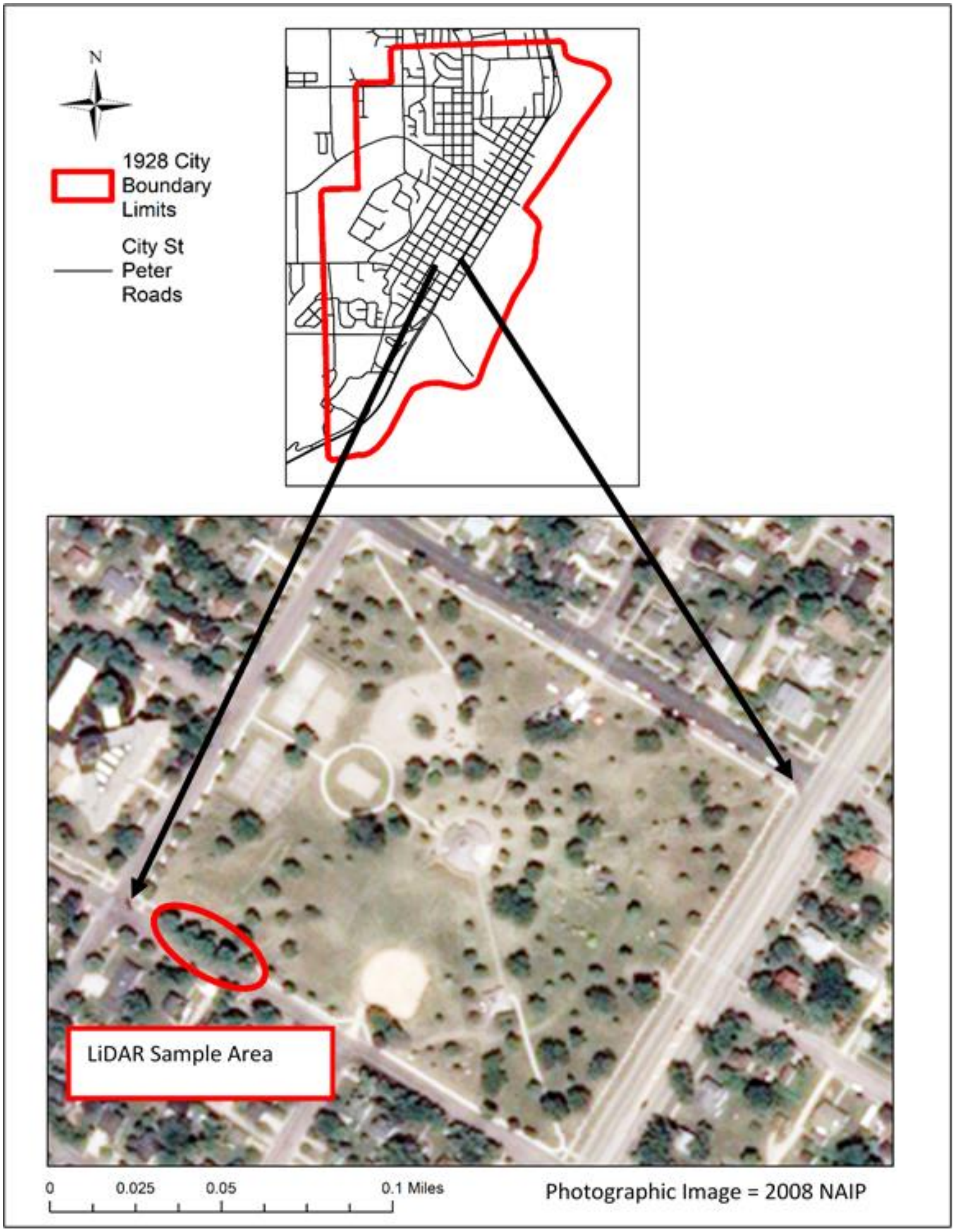

Figure 27. Location of sample LiDAR results

The accuracy of these metrics are limited by several factors. Firstly, forestry research LiDAR is typically collected with the leaves on; the research LiDAR was collected with the leaves off. Secondly, the LiDAR point cloud for the research was 0.19 points/ft^2; this is approximately ten times less dense than the minimum commonly used within LiDAR derived forest research, 1.96 points/ft^2 (Chen et al. 2006; Li et al. 2012; Ma, Su, and Guo 2017). Thirdly, even with improvement of the LiDAR data quality, there are still errors associated with the point cloud classification and therefore the potential to locate trees where none exist. Fourthly, the CHM segmentation is based on a paper that uses an algorithm where the research location is oak savannah woodland, not an urban forest. The only building structure was a fire lookout, which was removed from the data prior to the assessments (Chen et al. 2006). In addition, the point cloud segmentation is based on a paper that uses a segmentation algorithm where the research area is a mixed conifer forest, not an urban environment (Li et al. 2012).

Figure 28 shows an example area, located at Minnesota Square Park, of the CHM segmentation process and the map illustrates some of the issues discussed above. For example, it is possible to see areas (purple circle) where, due to incorrect point cloud classification, tree cloud points and therefore incorrect seedpoint locations are identified. Further, the red polygon areas represent the areas of individual trees as calculated during tree segmentation. As can be seen, these generally do not outline the areas of trees shown within the 2008 NAIP image and represented by the tree cloud points.

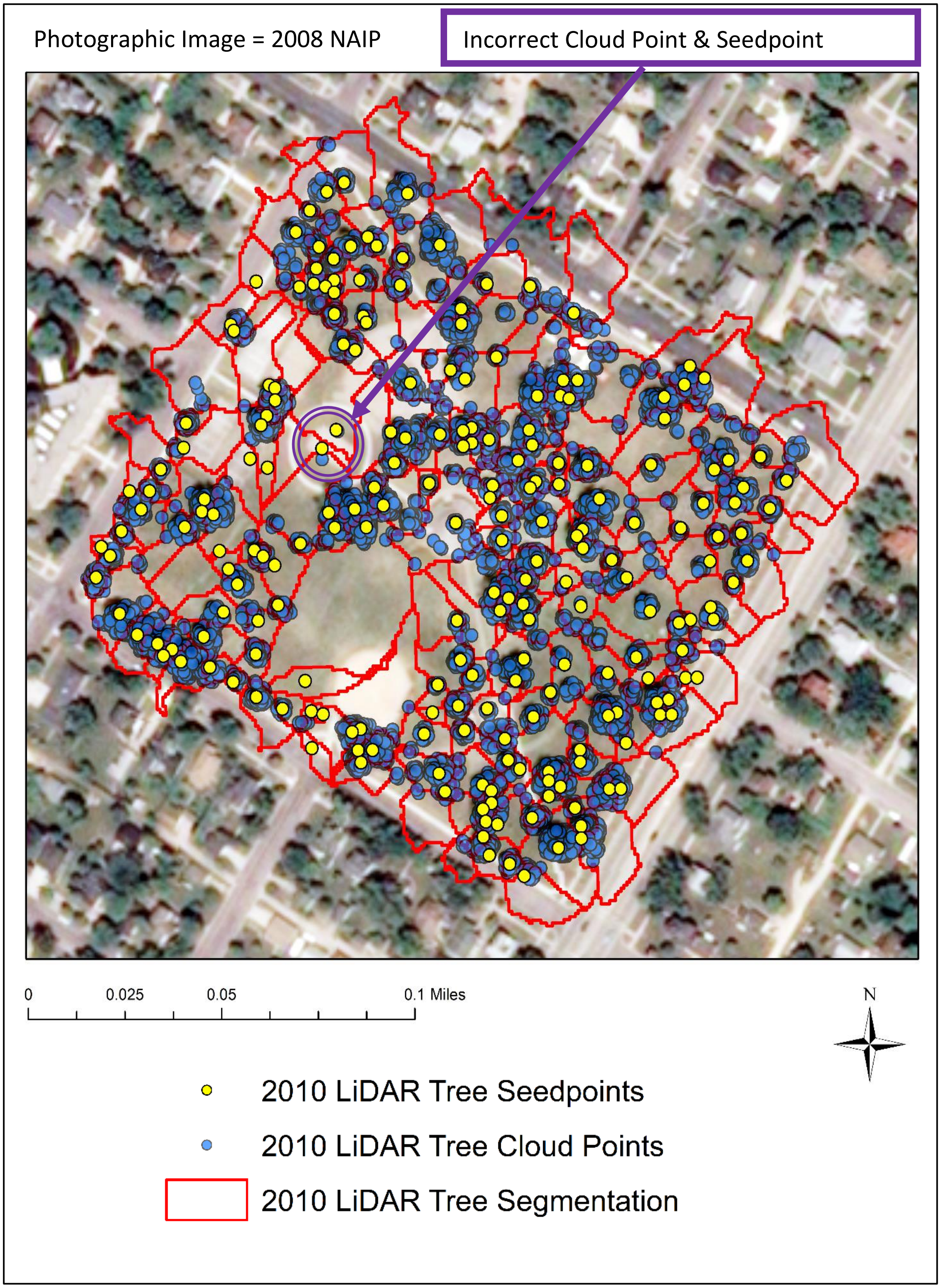

Figure 28. Minnesota Square Park; 2010 LiDAR CHM tree seedpoints, cloudpoints, and segmentation

Figures 29-31 demonstrate a 2D representation of the sample area, a 3D image, and a cross sectional area of individual trees detailed in Table 22 respectively. While the accuracy of the metrics cannot be assessed, it is important to acknowledge the benefits that the 3D views of the urban forest offer, e.g., visual assessment for tree planting programs, etc. The results from the use of LiDAR data can only be improved with continued data capture using higher density LiDAR point clouds collected at leaf-on season.

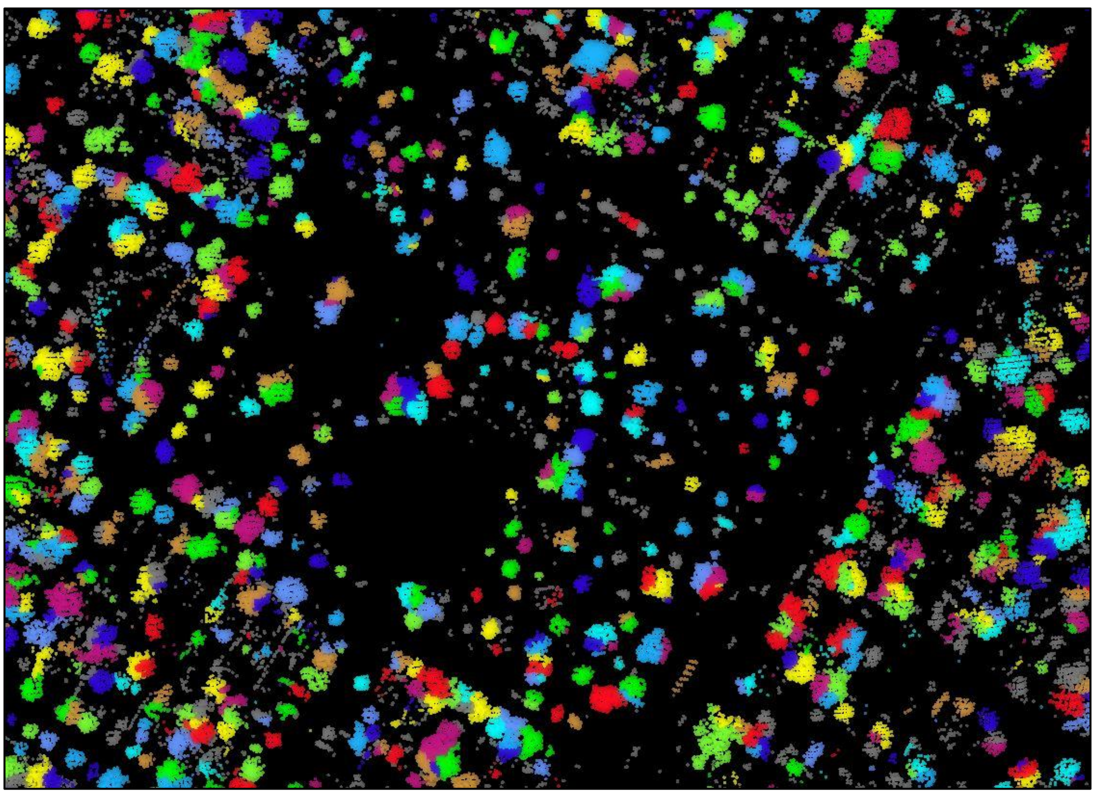

Figure 29. Minnesota Square Park; 2D LiDAR tree classification

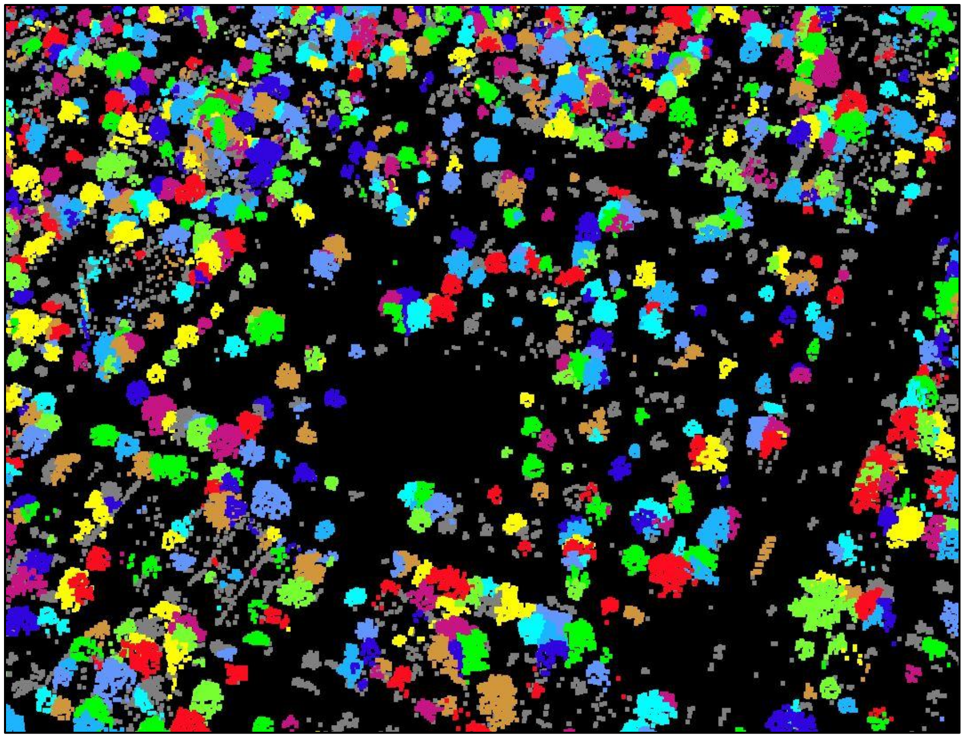

Figure 30. Minnesota Square Park; 3D LiDAR tree classification

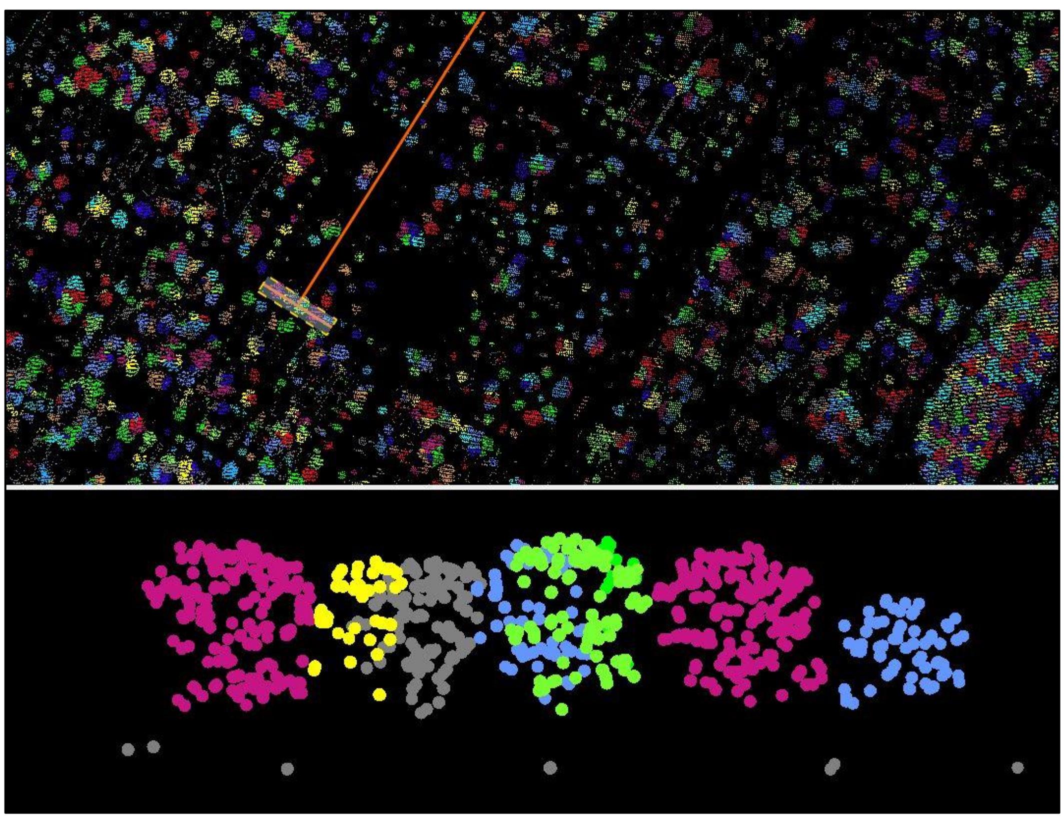

Figure 31. Minnesota Square Park; cross section of individual trees

5 Conclusions and Future Outlook

This research was undertaken to determine if there has been temporal change in the canopy cover within the boundary of the City of St Peter and if so, why and how. In addition, two methods were used to ascertain the canopy cover area for specific years.

The results have shown that the canopy cover extent has changed temporally both in size and location and that both OBIA and stratified random sampling results corroborate each other. The accuracy assessment results show that both OBIA and stratified random sampling can accurately determine urban forest canopy cover; however, it is important to select the appropriate photographic images and be aware that certain image types, e.g., scanned images, could potentially lead to lower accuracy results.

The canopy cover has steadily increased in size from 1938 to 2019 from ~20% to ~35% of total land cover and that change can be broken down into two distinct time zones pre 1995 (~20%-25%) and post 1995 (~35%). Canopy change detection showed that the 1998 tornado had the largest impact on canopy cover. Between 1995 and 2008 at least 45% of the canopy cover within the tornado tract was removed. With subsequent replanting an additional 10% of total canopy cover was added to the City of St Peter: 40% of this in the tract and 60% outside, leading to a total canopy cover of ~35% which has remained stable.

As well as the tornado tract, results show that canopy change has been dynamic within the City of St Peter, with only ~9% of canopy cover remaining canopy cover between 1938-2017 chiefly within the City of St Peter city center and the north east Minnesota River flood plain. New canopy has been created due to land use change in flood plain areas and as the City of St Peter has expanded to the north and west boundaries. It was observed however, that canopy cover has also been converted to non-canopy mainly before 1995 predominantly along the Minnesota River floodplain due to river course change and within the city center due to redevelopment.

The impact of tree disease on the canopy cover was undetectable due to the temporal and photographic image resolution; however, the canopy cover change results show consistent canopy cover coverage during the disease epidemics leading to a conjecture that planting or natural regeneration maintained the canopy cover size.

The LiDAR results proved valuable in a number of ways. Firstly, using the variation in height of the canopy cover, the path of the tornado was still visible within the City of St Peter and a canopy height model was created showing that the tallest canopy (>40ft) is situated along the floodplain and isolated spots within the City's center. Secondly, the LiDAR canopy cover density model verified the accuracy of the 2008 OBIA canopy cover data. Finally, tree metrics were calculated for the majority of trees within the City of St Peter. Whilst the validation of the individual tree metrics was not possible within the scope of this research project, the fact that it is possible to determine these metrics from remote sensing rather than ground assessment bodes well for future urban forest tree and canopy assessment.

Overall, the research has shown the value of using OBIA, stratified random sampling, and LiDAR to determine urban forest metrics. Stratified random sampling is an efficient accurate method to determine urban forest canopy cover area, while OBIA offers the ability to ascertain temporal canopy change leading to more detailed analysis. LiDAR offers the potential to extract more canopy and tree metrics for historical data via regression analysis, etc., but only if sample and independent variable data is present. As the current city forester, this research enables me to evaluate ecosystem services, plan future management of the urban forest, and educate the citizens of the City of St Peter on the present and historical forest canopy.

Before this research began there was no information known about the City of St Peter's total urban forest canopy cover. The only tree metrics known e.g., tree species and DBH, were limited to city boulevard trees located on the city ROW, a limited amount of the entire urban forest, and these were collected using ground assessment. Whilst the determination of the urban forest canopy is the first step, ultimately, as the city forester, my goal would be to have a complete tree inventory of all trees and metrics including individual tree species within the City of St Peter boundary.

Using ground assessment in the collection of this information would be highly unlikely if not impossible based on time and finance limitations. However, the use of remote geospatial technologies will likely make this possible. For example, current research into the use of LiDAR and hyperspectral images shows the future possibilities, by utilizing LiDAR to determine specific location and tree structure and hyperspectral data to determine individual tree species. Another benefit of the hyperspectral data is the determination of the health of the urban forest, e.g., detection of tree stress. This combination could provide a complete picture of the urban forest. In addition, with the advent and continuing increase in use of unmanned aerial vehicles (UAV) in combination with geospatial technologies, data collection and processing has the potential to become more local and data specific, thus leading to local agencies such as the City of St Peter ultimately being able to collect their own data.

References

Ahmadzadeh, R., S.S. Sindhu, K.V. Prasad, D.K. Das, and N.R. Sahoo. 2015. "Mapping and Cataloguing of Trees of Iari Campus, New Delhi, India Uisng Gis and Gps." *Indian Journal of Agricultural Sciences* 85 (1):131-136.

Alonzo, M., B. Bookhagen, and D.A. Roberts. 2014. "Urban Tree Species Mapping Using Hyperspectral and Lidar Data Fusion." *Remote Sensing of Environment* 148:70-83. doi: https://doi.org/10.1016/j.rse.2014.03.018.

Anderson, T., and S. Dragićević. 2015. "An Agent-Based Modeling Approach to Represent Infestation Dynamics of the Emerald Ash Borer Beetle." *Ecological Informatics* 30:97-109. doi: https://doi.org/10.1016/j.ecoinf.2015.09.003.

Bahe, M. 2018. "Case Study: Using Drones for Urban Forest Inventory and Health Assessment." Minnesota Society of Arboriculture Annual Conference, University of Minnesota, 10/18/18.

Baisantry, M., D.P. Shukla, and G. Bansal. 2017. "Evaluation of Object-Based Image Analysis Softwares for Segmentation in Remote Sensing Applications." Association of Geographic Information Laboratories in Europe, Wageningen, Netherlands, May 9-12, 2017.

Beck, V., and N. Dotzek. 2010. "Reconstruction of near-Surface Tornado Wind Fields from Forest Damage." *Journal of Applied Meteorology and Climatology* 49 (7):1517-1537. doi: 10.1175/2010JAMC2254.1.

BenDor, T.K., and S.S. Metcalf. 2006. "The Spatial Dynamics of Invasive Species Spread." *System Dynamics Review* 22 (1):27-50. doi: 10.1002/sdr.328.

Berland, A., D.L. Herrmann, and M.E. Hopton. 2016. "National Assessment of Tree City USA Participation According to Geography and Socioeconomic Characteristics." *Arboriculture & Urban Forestry* 42 (2):120-130.

Birdal, A.C., U. Avdan, and T. Türk. 2017. "Estimating Tree Heights with Images from an Unmanned Aerial Vehicle." *Geomatics, Natural Hazards and Risk* 8 (2):1144-1156. doi: 10.1080/19475705.2017.1300608.

Blaschke, T. 2010. "Object Based Image Analysis for Remote Sensing." *ISPRS Journal of Photogrammetry and Remote Sensing* 65 (1):2-16. doi: https://doi.org/10.1016/j.isprsjprs.2009.06.004.

Bloniarz, D.V., and R.T. Brooks. 2011. Preliminary Assessment of the Tornado Effects on Residential Street Canopy Cover, Temperature, and Humidity. edited by Northern Research Station USDA Forest Service: USDA Forest Service, Northern Research Station.

Blundell, S., D.D. Opiz, M. Morris, and R. Rjendran. 2008. "Feature Analyst V5.0." American Society for Photogrammetry and Remote Sensing, Porland, Oregon, April 28-May 02, 2008.

Bodnaruk, E.W., C.N. Kroll, Y. Yang, S. Hirabayashi, D.J. Nowak, and T.A. Endreny. 2017. "Where to Plant Urban Trees? A Spatially Explicit Methodology to Explore Ecosystem Service Tradeoffs." *Landscape and Urban Planning* 157:457-467. doi: 10.1016/j.landurbplan.2016.08.016.

Brasier, C., and K. Buck. 2001. "Rapid Evolutionary Changes in a Globally Invading Fungal Pathogen (Dutch Elm Disease)." *Biological Invasions* 3 (3):223-233.

Broders, K., A. Boraks, L. Barbison, J. Brown, and G.J. Boland. 2015. "Recent Insights into the Pandemic Disease Butternut Canker Caused by the Invasive Pathogen Ophiognomonia Clavigignenti-Juglandacearum." *Forest Pathology* 45 (1):1-8. doi: doi:10.1111/efp.12161.

Burgess, D., K. Ortega, G. Stumpf, G. Garfield, C. Karstens, T. Meyer, B. Smith, D. Speheger, J. Ladue, and R. Smith. 2014. "20 May 2013 Moore, Oklahoma, Tornado: Damage Survey and Analysis." *Weather and Forecasting* 29 (5):1229-1237.

Byholm, B. 2017. "Remote Sensing of World War Ii Era Unexploded Bombs Using Object-Based Image Analysis and Multi-Temporal Datasets: A Case Study of the Fort Myers Bombing and Gunnery Range." Masters, Geography Department, Minnesota State University.

Campana, R.J. 1999. *Arboriculture: History and Development in North America*. East Lansing: Michigan State University Press.

Chang, K.-T. 2016. *Introduction to Geographic Information Systems*. New York: McGraw-Hill Education.

Chen, G., E. Ozelkan, K.K. Singh, J. Zhou, M.R. Brown, and R.K. Meentemeyer. 2017. "Uncertainties in Mapping Forest Carbon in Urban Ecosystems." *J Environ Manage* 187:229-238. doi: 10.1016/j.jenvman.2016.11.062.

Chen, Q., D. Baldocchi, P. Gong, and M. Kelly. 2006. "Isolating Individual Trees in a Savanna Woodland Using Small Footprint Lidar Data." *Photogrammetric Engineering & Remote Sensing* 72 (8):923-932.

City of Saint Peter. 2017. "City of Saint Peter Statistics." City of Saint Peter, accessed 19 April 2017.

City of Saint Peter. 2018. Species Distibution of Public Trees. edited by City of Saint Peter. City of Saint Peter.

Congalton, R.G., and K. Green. 2019. *Assessing the Accuracy of Remotely Sensed Data: Principles and Practices*. 3rd ed. Boca Raton: CRC Press/Taylor & Francis.

Conway, T.M., and V. Yip. 2016. "Assessing Residents' Reactions to Urban Forest Disservices: A Case Study of a Major Storm Event." *Landscape and Urban Planning* 153:1-10. doi: https://doi.org/10.1016/j.landurbplan.2016.04.016.

Cowett, F.D., and N. Bassuk. 2017. "Street Tree Diversity in Three Northeastern U.S. States." *Arboriculture & Urban Forestry* 43 (1):1-14.

Cuddington, K., S. Sobek-Swant, J.C. Crosthwaite, D.B. Lyons, and B.J. Sinclair. 2018. "Probability of Emerald Ash Borer Impact for Canadian Cities and North America: A Mechanistic Model." *Biological Invasions* 20 (9):2661-2677. doi: 10.1007/s10530-018-1725-0.

Dadea, C., A. Russo, M. Tagliavini, T. Mimmo, and S. Zerbe. 2017. "Tree Species as Tools for Biomonitoring and Phytoremediation in Urban Envrionments: A Review with Special Regard to Heavy Metals." *Arboriculture & Urban Forestry* 43 (4):155-167.

Davidson, W., and L.K. Rieske. 2016. "Establishment of Classical Biological Control Targeting Emerald Ash Borer Is Facilitated by Use of Insecticides, with Little

Effect on Native Arthropod Communities." *Biological Control* 101:78-86. doi: 10.1016/j.biocontrol.2016.06.010.

Delshammar, T., J. Östberg, and C. Öxell. 2015. "Urban Trees and Ecosystem Disservices-a Pilot Study Using Complaints Records from Three Swedish Cities." *Arboriculture & Urban Forestry* 41 (4):187-193.

Edmondson, J.L., I. Stott, Z.G. Davies, K.J. Gaston, and J.R. Leake. 2016. "Soil Surface Temperatures Reveal Moderation of the Urban Heat Island Effect by Trees and Shrubs." *Sci Rep* 6:33708. doi: 10.1038/srep33708.

Arcgis 10.5 Help 10.5. ESRI, Redlands, CA.

Fahrner, S.J., M. Abrahamson, R.C. Venette, and B.H. Aukema. 2017. "Strategic Removal of Host Trees in Isolated, Satellite Infestations of Emerald Ash Borer Can Reduce Population Growth." *Urban Forestry & Urban Greening* 24:184-194. doi: 10.1016/j.ufug.2017.03.017.

Fujita, T.T. 1971. "Proposed Characterization of Tornadoes and Hurricanes by Area and Intensity."

Galvin, M.F., and D. Bleil. 2004. "Relationship among Tree Canopy Quantitiy Community Demographics, and Tree City USA Program Participation in Maryland, U.S." *Journal of Aboriculture* 30 (6):321-327.

Gerhold, H.D. 2007. "Origins of Urban Forestry." In, 1-23. Dordrecht: Springer Netherlands.

Giblin, C.P., and J.H. Gillman. 2009. *Pruning Young Elms*. St Paul, MN: Urban Forestry & Horticulture Research Institute.

Gokaraju, B., A.C. Turlapaty, D.A. Doss, R.L. King, and N.H. Younan. 2015. "Change Detection Analysis of Tornado Disaster Using Conditional Copulas and Data Fusion for Cost-Effective Disaster Management." Applied Imagery Pattern Recognition Workshop (AIPR), 2015 IEEE.

Grant, S. 2015. "The Right Tree in the Right Place: Using Gis to Maximize the Net Benefits from Urban Forests." Master Degree in Geographical Information Sciences, Physical Geography and Ecosystem Science; Centre for Geographical Information Systems, Lund University.

Lidar360 User Guide. GreenValley International Ltd, Berkeley, California.

Haralick, R.M., K. Shanmugam, and I. Dinstein. 1973. "Textural Features for Image Classification." *IEEE Transactions on systems, man, and cybernetics* (6):610-621.

Harris, R.W. 1983. *Arboriculture: Care of Trees, Shrubs, and Vines in the Landscape*. Englewood Cliffs, New Jersey 07632: Prentice-Hall, Inc.

Hauer, R.J., and W.D. Peterson. 2017. "Effects of Emerald Ash Borer on Municipal Forestry Budgets." *Landscape and Urban Planning* 157:98-105. doi: 10.1016/j.landurbplan.2016.05.023.

Hawthorne, T.L., V. Elmore, A. Strong, P. Bennett-Martin, J. Finnie, J. Parkman, T. Harris, J. Singh, L. Edwards, and J. Reed. 2015. "Mapping Non-Native Invasive Species and Accessibility in an Urban Forest: A Case Study of Participatory Mapping and Citizen Science in Atlanta, Georgia." *Applied Geography* 56:187-198. doi: 10.1016/j.apgeog.2014.10.005.

Hay, G.J., T. Blaschke, S. Lang, and G. Hay. 2008. *Object-Based Image Analysis: Spatial Concepts for Knowledge-Driven Remote Sensing Applications*. 1. Aufl. ed. Berlin, Heidelberg: Springer-Verlag.

Hexagon Geospatial. 2019a. "Accuracy Assessment." Hexagon Geospatial, accessed 01/26/2019. https://hexagongeospatial.fluidtopics.net/reader/uOKHREQkd_XR9iPo9Y_Ijw/rLomfBPytwxOz0sxagEMeg.

Hexagon Geospatial. 2019b. "Matrix Analysis." Hexagon Geopatial, accessed 03/27/19. https://hexagongeospatial.fluidtopics.net/reader/uOKHREQkd_XR9iPo9Y_ljw/FHwHTMam8EWJP5P8tfpjig.

Hoffman, R.R., and A.B. Markman. 2001. *Interpreting Remote Sensing Imagery: Human Factors*. Boca Raton, Fla: Lewis Publishers.

Holland, A.P., A.J. Riordan, and E.C. Franklin. 2006. "A Simple Model for Simulating Tornado Damage in Forests." *Journal of Applied Meteorology and Climatology* 45:1597-1611.

Hovi, A., L. Korhonen, J. Vauhkonen, and I. Korpela. 2016. "Lidar Waveform Features for Tree Species Classification and Their Sensitivity to Tree- and Acquisition Related Parameters." *Remote Sensing of Environment* 173:224-237. doi: https://doi.org/10.1016/j.rse.2015.08.019.

Hussain, M., D. Chen, A. Cheng, H. Wei, and D. Stanley. 2013. "Change Detection from Remotely Sensed Images: From Pixel-Based to Object-Based Approaches."

ISPRS Journal of Photogrammetry and Remote Sensing 80:91-106. doi: 10.1016/j.isprsjprs.2013.03.006.

Jennings, S., N. Brown, and D. Sheil. 1999. "Assessing Forest Canopies and Understorey Illumination: Canopy Closure, Canopy Cover and Other Measures." *Forestry: An International Journal of Forest Research* 72 (1):59-74.

Jiang, B., C.-Y. Chang, and W.C. Sullivan. 2014. "A Dose of Nature: Tree Cover, Stress Reduction, and Gender Differences." *Landscape and Urban Planning* 132:26-36. doi: 10.1016/j.landurbplan.2014.08.005.

Jiang, B., D. Li, L. Larsen, and W.C. Sullivan. 2014. "A Dose-Response Curve Describing the Relationship between Urban Tree Cover Density and Self-Reported Stress Recovery." *Environment and Behavior*:1-23. doi: 10.1177/0013916514552321.

Jonnes, J. 2016. *Urban Forests : A Natural History of Trees and People in the American Cityscape*. New York, New York: Viking.

Karstens, C.D., W.A. Gallus Jr, B.D. Lee, and C.A. Finley. 2013. "Analysis of Tornado-Induced Tree Fall Using Aerial Photography from the Joplin, Missouri, and Tuscaloosa–Birmingham, Alabama, Tornadoes of 2011." *Journal of Applied Meteorology and Climatology* 52 (5):1049-1068.

Kingfield, D.M., and K.M. de Beurs. 2017. "Landsat Identification of Tornado Damage by Land Cover and an Evaluation of Damage Recovery in Forests." *Journal of Applied Meteorology and Climatology* 56 (4):965-987. doi: 10.1175/jamc-d-16-0228.1.

Knight, J., T. Host, and L. Rampi. 2016. 2015 Urban Tree Canopy Assessment Twin Cities Metropolitan Area. University of Minnesota.

Kondo, M.C., S. Han, G.H. Donovan, and J.M. MacDonald. 2017. "The Association between Urban Trees and Crime: Evidence from the Spread of the Emerald Ash Borer in Cincinnati." *Landscape and Urban Planning* 157:193-199. doi: 10.1016/j.landurbplan.2016.07.003.

Konijnendijk, C.C., K. Nilsson, T.B. Randrup, and J. Schipperijn. 2005. *Urban Forests and Trees: A Reference Book.* 1. Aufl.;1; ed. Berlin, Heidelberg: Springer-Verlag.

Konijnendijk, C.C., R.M. Ricard, A. Kenney, and T.B. Randrup. 2006. "Defining Urban Forestry – a Comparative Perspective of North America and Europe." *Urban Forestry & Urban Greening* 4 (3):93-103. doi: https://doi.org/10.1016/j.ufug.2005.11.003.

Korhonen, L., and F. Morsdorf. 2014. "Estimation of Canopy Cover, Gap Fraction and Leaf Area Index with Airborne Laser Scanning." *Forestry Applications of Airborne Laser Scanning: Concepts and Case Studies* 27:397.

Lefsky, M.A., W.B. Cohen, G.G. Parker, and D.J. Harding. 2002. "Lidar Remote Sensing for Ecosystem Studies." *BioScience* 52 (1):19-30.

Li, S., F. Yuan, S.T. Ata-UI-Karim, H. Zheng, T. Cheng, X. Liu, Y. Tian, Y. Zhu, W. Cao, and Q. Cao. 2019. "Combining Color Indices and Textures of Uav-Based Digital Imagery for Rice Lai Estimation." *Remote Sensing* 11 (15):1763.

Li, W., Q. Guo, M.K. Jakubowski, and M. Kelly. 2012. "A New Method for Segmenting Individual Trees from the Lidar Point Cloud." *Photogrammetric Engineering & Remote Sensing* 78 (1):75-84.

Li, X., and G. Shao. 2014. "Object-Based Land-Cover Mapping with High Resolution Aerial Photography at a County Scale in Midwestern USA." *Remote Sensing* 6 (11):11372.

Lillesand, T.M., R.W. Kiefer, and J.W. Chipman. 2015. *Remote Sensing and Image Interpretation*. 7th ed. Hoboken, NJ: John Wiley & Sons.

Lilly, S.J. 2010. *Arborists' Certification Study Guide*. Champaign, IL: International Society of Arboriculture.

Lim, K., P. Treitz, M. Wulder, B. St-Onge, and M. Flood. 2003. "Lidar Remote Sensing of Forest Structure." *Progress in Physical Geography* 27 (1):88-106. doi: 10.1191/0309133303pp360ra.

Lindberg, E., and J. Holmgren. 2017. "Individual Tree Crown Methods for 3d Data from Remote Sensing." *Current Forestry Reports* 3 (1):19-31. doi: 10.1007/s40725-017-0051-6.

Ma, Q., Y. Su, and Q. Guo. 2017. "Comparison of Canopy Cover Estimations from Airborne Lidar, Aerial Imagery, and Satellite Imagery." *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing* 10 (9):4225-4236. doi: 10.1109/jstars.2017.2711482.

McCullough, D.G., and R.J. Mercader. 2012. "Evaluation of Potential Strategies to Slow Ash Mortality (Slam) Caused by Emerald Ash Borer (Agrilus Planipennis): Slam in an Urban Forest." *International Journal of Pest Management* 58 (1):9-23. doi: 10.1080/09670874.2011.637138.

Mekik, C., and M. Arslanoglu. 2009. "Investigation on Accuracies of Real Time Kinematic Gps for Gis Applications." *Remote Sensing* 1 (1):22-35. doi: 10.3390/rs1010022.

Melaas, E.K., J.A. Wang, D.L. Miller, and M.A. Friedl. 2016. "Interactions between Urban Vegetation and Surface Urban Heat Islands: A Case Study in the Boston Metropolitan Region." *Environmental Research Letters* 11 (5):054020. doi: 10.1088/1748-9326/11/5/054020.

Meneguzzo, D.M., G.C. Liknes, and M.D. Nelson. 2013. "Mapping Trees Outside Forests Using High-Resolution Aerial Imagery: A Comparison of Pixel- and Object-Based Classification Approaches." *Environmental Monitoring and Assessment* 185 (8):6261-6275. doi: 10.1007/s10661-012-3022-1.

Mercader, R.J., N.W. Siegert, A.M. Liebhold, and D.G. McCullough. 2009. "Dispersal of the Emerald Ash Borer, Agrilus Planipennis, in Newly-Colonized Sites." *Agricultural and Forest Entomology* 11 (4):421-424. doi: 10.1111/j.1461-9563.2009.00451.x.

Miller, R.W. 1988. *Urban Forestry: Planning and Managing Urban Greenspaces*. Englewood Cliffs, New Jersey 07632: Prentice-Hall, Inc.

MNDNR. 2019a. "Insects in Minnesota Confused with Emerald Ash Borer." Minnesota Department of Natural Resources, accessed 11/02/19.

https://conservancy.umn.edu/bitstream/handle/11299/199779/EAB-others-2018.pdf?sequence=1&isAllowed=y.

MNDNR. 2019b. Mndnr Forest Stand Inventory. edited by Minnesota department of Natural Resources. St Paul, MN: Minnesota department of Natural Resources - Division of Forestry.

MNDOT. 2006. Mndot Historic Bridge Management Plan (Bridge Number: 4930). edited by Minnesota Department of Transport. St Paul, MN: MNDOT.

MnGeo. 2010. "Metadata: Lidar Elevation, Minnesota River Basin, Southwest Minnesota. 2010.". MnGeo, accessed 5th April 2018. ftp://ftp.gisdata.mn.gov/pub/gdrs/data/pub/us_mn_State_mngeo/elev_lidar_swmn2010/metadata/metadata.html.

Morgan, J.L., and S.E. Gergel. 2010. "Quantifying Historic Landscape Heterogeneity from Aerial Photographs Using Object-Based Analysis." *Landscape Ecology* 25 (7):985-998. doi: 10.1007/s10980-010-9474-1.

Morgan, J.L., and S.E. Gergel. 2013. "Automated Analysis of Aerial Photographs and Potential for Historic Forest Mapping." *Canadian Journal of Forest Research* 43 (8):699-710. doi: 10.1139/cjfr-2012-0492.

Morgan, J.L., S.E. Gergel, and N.C. Coops. 2010. "Aerial Photography: A Rapidly Evolving Tool for Ecological Management." *BioScience* 60 (1):47-59.

Morin, R.S., K.W. Gottschalk, M.E. Ostry, and A.M. Liebhold. 2018. "Regional Patterns of Declining Butternut (Juglans Cinerea L.) Suggest Site Characteristics for Restoration." *Ecology and evolution* 8 (1):546-559.

Moskal, L.M., D.M. Styers, and M. Halabisky. 2011. "Monitoring Urban Tree Cover Using Object-Based Image Analysis and Public Domain Remotely Sensed Data." *Remote Sensing* 3 (12):2243-2262. doi: 10.3390/rs3102243.

Muirhead, J.R., B. Leung, C. van Overdijk, D.W. Kelly, K. Nandakumar, K.R. Marchant, and H.J. MacIsaac. 2006. "Modelling Local and Long-Distance Dispersal of Invasive Emerald Ash Borer Agrilus Planipennis (Coleoptera) in North America." *Diversity and Distributions* 12 (1):71-79.

Mullen, K., F. Yuan, and M. Mitchell. 2018. "The Mountain Pine Beetle Epidemic in the Black Hills, South Dakota: The Consequences of Long Term Fire Policy, Climate Change and the Use of Remote Sensing to Enhance Mitigation." *Journal of Geography and Geology* 10 (1).

Myint, S.W., P. Gober, A. Brazel, S. Grossman-Clarke, and Q. Weng. 2011. "Per-Pixel Vs. Object-Based Classification of Urban Land Cover Extraction Using High Spatial Resolution Imagery." *Remote Sensing of Environment* 115 (5):1145-1161. doi: 10.1016/j.rse.2010.12.017.

Nagel, P., B. Cook, and F. Yuan. 2014. "High Spatial-Resolution Land Cover Classification and Wetland Mapping over Large Areas Using Integrated Geospatial Technologies." *International Journal of Remote Sensing Applications* 4 (2):71-86.

Nagel, P., and F. Yuan. 2016. "High-Resolution Land Cover and Impervious Surface Classifications in the Twin Cities Metropolitan Area with Naip Imagery." *Photogrammetric Engineering & Remote Sensing* 82 (1):63-71.

NOAA. 2017. Gis Tornado Shapefile. edited by NOAA: NOAA.

Nowak, D.J. 2008. "Assessing Urban Forest Structure: Summary and Conclusions." *Arboriculture & Urban Forestry* 34 (6):391-392.

Nowak, D.J., and J.F. Dwyer. 2007. "Understanding the Benefits and Costs of Urban Forest Ecosystems." In, 25-46. Dordrecht: Springer Netherlands.

Nowak, D.J., and E.J. Greenfield. 2010. "Evaluating the National Land Cover Database Tree Canopy and Impervious Cover Estimates across the Conterminous United States: A Comparison with Photo-Interpreted Estimates." *Environ Manage* 46 (3):378-90. doi: 10.1007/s00267-010-9536-9.

Nowak, D.J., R.E. Hoehn, A.R. Bodine, E.J. Greenfield, and J. O'Neil-Dunne. 2013. "Urban Forest Structure, Ecosystem Services and Change in Syracuse, Ny." *Urban Ecosystems* 19 (4):1455-1477. doi: 10.1007/s11252-013-0326-z.

Nowak, D.J., M.H. Noble, S.M. Sisinni, and J.F. Dwyer. 2001. "People and Trees: Assessing the Us Urban Forest Resource." *Journal of Forestry* 99 (3):37-42.

Nowak, D.J., R.A. Rowntree, E.G. McPherson, S.M. Sisinni, E.R. Kerkmann, and J.C. Stevens. 1996. "Measuring and Analyzing Urban Tree Cover." *Landscape and Urban Planning* 36:49-57.

Nowak, D.J., W.J. T., J. Baldwin, and J. Bond. 2015. "Simple Street Tree Sampling." *Arboriculture & Urban Forestry* 41 (6):346-354.

O'Brian, M.A. 2003. "Feature Extraction with Vls Feature Analyst Sytem." Reston, VA.

Olokeogun, O.S., O.O. Akintola, and E.K. Abodunrin. 2016. "The Potential of Gis as a Management Tool for Avenue Trees Population in Small Communities; a Case

Study of Idi-Shin Community, Ibadan, Nigeria." *ISPRS - International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences* XLI-B6:283-288. doi: 10.5194/isprsarchives-XLI-B6-283-2016.

Olowokudejo, T., and J. Piwowar. 2013. "Anthropogenic Disturbance Extraction Using Object-Oriented Image Classification Software: A Comparison of Overwatch Feature Analyst and Definiens Developer." *Prairie Perspectives: Geographical Essays* 16:1-9.

Omasa, K., F. Hosoi, T.M. Uenishi, Y. Shimizu, and Y. Akiyama. 2007. "Three-Dimensional Modeling of an Urban Park and Trees by Combined Airborne and Portable on-Ground Scanning Lidar Remote Sensing." *Environmental Modeling & Assessment* 13 (4):473-481. doi: 10.1007/s10666-007-9115-5.

Opitz, D., and S. Blundell. 2006. "Object Recognition and Feature Extraction from Imagery: The Feature Analyst® Approach." *Photogrammetry, Remote Sensing and Spatial Sciences* 36 (4):1-6.

Opitz, D., and S. Blundell. 2008. "Object Recognition and Image Segmentation: The Feature Analyst® Approach." In *Object-Based Image Analysis*, edited by Thomas Blaschke, Stefan Lang and Geoffrey J. Hay, 153-167. Berlin, Heidelberg: Springer Berlin Heidelberg.

Ostry, M., and K. Woeste. 2004. "Spread of Butternut Canker in North America, Host Range, Evidence of Resistance within Butternut Populations and Conservation Genetics." In: Michler, CH; Pijut, PM; Van Sambeek, JW; Coggeshall, MV; Seifert, J.; Woeste, K.; Overton, R.; Ponder, F., Jr., eds. Proceedings of the 6th

Walnut Council Research Symposium; Gen. Tech. Rep. NC-243. St. Paul, MN: US Department of Agriculture, Forest Service, North Central Research Station. 114-120.

Overwatch Systems Ltd. 2013. Feature Analyst® 5.1.X for Arcgis® Tutorial. 1-158.

Feature Analyst™ 5.2.0 for Arcgis® Reference Guide 5.2.0 (OBIA). Overwatch Systems Ltd, Sterling, VA.

Parmehr, E.G., M. Amati, and C.S. Fraser. 2016. "Mapping Urban Tree Canopy Cover Using Fused Airborne Lidar and Satellite Imagery Data." *ISPRS Annals of Photogrammetry, Remote Sensing and Spatial Information Sciences* III-7:181-186. doi: 10.5194/isprsannals-III-7-181-2016.

Plowright, A.A., N.C. Coops, B.N.I. Eskelson, S.R.J. Sheppard, and N.W. Aven. 2016. "Assessing Urban Tree Condition Using Airborne Light Detection and Ranging." *Urban Forestry & Urban Greening* 19:140-150. doi: 10.1016/j.ufug.2016.06.026.

Prasad, A.M., L.R. Iverson, M.P. Peters, J.M. Bossenbroek, S.N. Matthews, T. Davis Sydnor, and M.W. Schwartz. 2010. "Modeling the Invasive Emerald Ash Borer Risk of Spread Using a Spatially Explicit Cellular Model." *Landscape Ecology* 25 (3):353-369. doi: 10.1007/s10980-009-9434-9.

Pu, R., S. Landry, and Q. Yu. 2018. "Assessing the Potential of Multi-Seasonal High Resolution Pléiades Satellite Imagery for Mapping Urban Tree Species." *International Journal of Applied Earth Observation and Geoinformation* (71):144-158. doi: 10.1016/j.jag.2018.05.005.

Qiu, X., S.-S. Wu, and X. Miao. 2014. "Incorporating Road and Parcel Data for Object-Based Classification of Detailed Urban Land Covers from Naip Images." *GIScience & remote sensing* 51 (5):498-520.

Lastools 2019. rapidlasso, Germany.

Rautiainen, M., P. Stenberg, and T. Nilson. 2005. "Estimating Canopy Cover in Scots Pine Stands." *Silva Fennica* 39 (1):137-142.

Rees, G. 2013. *Physical Principles of Remote Sensing*. 3rd ed. Cambridge;New York;: Cambridge University Press.

Ricard, R.M. 2005. "Shade Trees and Tree Wardens: Revising the History of Urban Forestry." *Journal of Forestry* 103 (5):230.

Richardson, J.J., and L.M. Moskal. 2014. "Uncertainty in Urban Forest Canopy Assessment: Lessons from Seattle, Wa, USA." *Urban Forestry & Urban Greening* 13 (1):152-157. doi: 10.1016/j.ufug.2013.07.003.

Rosenow, J., and M. Yager. 2007. "Tree City USA." In *Urban and Community Forestry in the Northeast*, edited by John E. Kuser, 419-427. New York, NY: Springer.

Roy, S., J. Byrne, and C. Pickering. 2012. "A Systematic Quantitative Review of Urban Tree Benefits, Costs, and Assessment Methods across Cities in Different Climatic Zones." *Urban Forestry & Urban Greening* 11 (4):351-363. doi: https://doi.org/10.1016/j.ufug.2012.06.006.

Ryherd, S., and C. Woodcock. 1996. "Combining Spectral and Texture Data in the Segmentation of Remotely Sensed Images." *Photogrammetric engineering and remote sensing* 62 (2):181-194.

Secord, J., and A. Zakhor. 2007. "Tree Detection in Urban Regions Using Aerial Lidar and Image Data." *IEEE Geoscience and Remote Sensing Letters* 4 (2):196-200. doi: 10.1109/LGRS.2006.888107.

Shrestha, R., and R.H. Wynne. 2012. "Estimating Biophysical Parameters of Individual Trees in an Urban Environment Using Small Footprint Discrete-Return Imaging Lidar." *Remote Sensing* 4 (12):484-508. doi: 10.3390/rs4020484.

Siegert, N.W., D.G. McCullough, R.J. Mercader, and A.M. Liebhold. 2011. "Simulating the Effectiveness of Three Potential Management Options to Slow the Spread of Emerald Ash Borer (Agrilus Planipennis) Populations in Localized Outlier Sites." *Canadian Journal of Forest Research* 41 (2):254-264. doi: 10.1139/X10-201.

Irfanview 4.52 -64 bit. Irfan Skiljan, 2700 Wiener Neustadt, Austria.

Song, Y., J. Imanishi, T. Sasaki, K. Ioki, and Y. Morimoto. 2016. "Estimation of Broad-Leaved Canopy Growth in the Urban Forested Area Using Multi-Temporal Airborne Lidar Datasets." *Urban Forestry & Urban Greening* 16:142-149. doi: 10.1016/j.ufug.2016.02.007.

Spei, B.A., and D.M. Kashian. 2017. "Potential for Persistence of Blue Ash in the Presence of Emerald Ash Borer in Southeastern Michigan." *Forest Ecology and Management* 392:137-143. doi: 10.1016/j.foreco.2017.02.053.

Strobel, G.A., and G.N. Lanier. 1981. "Dutch Elm Disease." *Scientific American* 245 (2):56-67.

Strunk, J.L., J.R. Mills, P. Ries, H. Temesgen, and L. Jeroue. 2016. "An Urban Forest-Inventory-and-Analysis Investigation in Oregon and Washington." *Urban Forestry & Urban Greening* 18:100-109. doi: 10.1016/j.ufug.2016.04.006.

Sumnall, M.J., R.A. Hill, and S.A. Hinsley. 2016. "Comparison of Small-Footprint Discrete Return and Full Waveform Airborne Lidar Data for Estimating Multiple Forest Variables." *Remote Sensing of Environment* 173:214-223. doi: https://doi.org/10.1016/j.rse.2015.07.027.

Tang, S., P. Dong, and B.P. Buckles. 2013. "Three-Dimensional Surface Reconstruction of Tree Canopy from Lidar Point Clouds Using a Region-Based Level Set Method." *International Journal of Remote Sensing* 34 (4):1373-1385. doi: 10.1080/01431161.2012.720046.

Tewkesbury, A.P., A.J. Comber, N.J. Tate, A. Lamb, and P.F. Fisher. 2015. "A Critical Synthesis of Remotely Sensed Optical Image Change Detection Techniques." *Remote Sensing of Environment* 160:1-14. doi: 10.1016/j.rse.2015.01.006.

Thenkabail, P.S., J.G. Lyon, and A. Huete. 2011. *Hyperspectral Remote Sensing of Vegetation*. 1st ed: CRC press.

Townsend, A., S. Bentz, and L. Douglass. 2005. "Evaluation of 19 American Elm Clones for Tolerance to Dutch Elm Disease." *Journal of Environmental Horticulture* 23 (1):21-24.

Ucar, Z., P. Bettinger, K. Merry, J. Siry, J.M. Bowker, and R. Akbulut. 2016. "A Comparison of Two Sampling Approaches for Assessing the Urban Forest

Canopy Cover from Aerial Photography." *Urban Forestry & Urban Greening* 16:221-230. doi: 10.1016/j.ufug.2016.03.001.

Ulrich, R.S. 1984. "View through a Window May Influence Recovery from Surgery." *Science* 224 (4647):420-421.

University of Washington, C.o.t.E. 2018. "Human Dimentions of Urban Forestry and Urban Greening." University of Washington, accessed 13th April 2019.

USDA. 2011. "I-Tree Canopy Technical Notes." U.S.D.A. Forest Service, accessed 03/29/19.

USDA. 2018a. "About I-Tree." U.S.D.A. Forest Service, accessed March 16 2018. itreetools.org/about.php.

USDA. 2018b. "I-Tree: Climate Change Resource Center." U.S.D.A. Forest Service, accessed March 16 2018. https://www.fs.usda.gov/ccrc/tools/i-tree.

I-Tree Canopy v6.1. U.S.D.A. Forest Service.

Veteto, W. 2019a. "Feature Analyst Questions About Texture & Vector to Raster Tool." 08/12/2019.

Veteto, W. 2019b. "Feature Analyst Scanned Image ", 10/21/2019.

Vogt, J., R.J. Hauer, and B.C. Fischer. 2015. "The Costs of Maintaining and Not Maintaining the Urban Forest: A Review of the Urban Forest and Arboriculture Literature." *Arboriculture & Urban Forestry* 41 (6):293-323.

Voss, M., and R. Sugumaran. 2008. "Seasonal Effect on Tree Species Classification in an Urban Environment Using Hyperspectral Data, Lidar, and an Object- Oriented Approach." *Sensors* 8 (5):3020.

Walker, J.S., and J.M. Briggs. 2007. "An Object-Oriented Approach to Urban Forest Mapping in Phoenix." *Photogrammetric Engineering & Remote Sensing* 73 (5):577-583. doi: 10.14358/PERS.73.5.577.

Walton, J.T., D.J. Nowak, and E.J. Greenfield. 2008. "Assessing Urban Forest Canopy Cover Using Airborne or Satellite Imagery." *International Society of Arboriculture* 34 (6):334-340.

Wang, G., and Q. Weng. 2014. *Remote Sensing of Natural Resources*. Boca Raton: CRC Press.

Ward, K.T., and G.R. Johnson. 2007. "Geospatial Methods Provide Timely and Comprehensive Urban Forest Information." *Urban Forestry & Urban Greening* 6 (1):15-22. doi: 10.1016/j.ufug.2006.11.002.

Wolowicz, R.S., and M. Gera. 2007. "Tree Inventory and Systematic Management." In *Urban and Community Forestry in the Northeast*, edited by John E. Kuser, 119-131. New York, NY: Springer.

Wood, J.P. 1999. "Tree Inventories and Gis in Urban Forestry." Master in Forestry, Virginia Polytechnic Institute and State University.

Wulder, M. 1998. "Optical Remote-Sensing Techniques for the Assessment of Forest Inventory and Biophysical Parameters." *Progress in Physical Geography* 22 (4):449-476. doi: 10.1177/030913339802200402.

Yao, W., P. Krzystek, and M. Heurich. 2012. "Tree Species Classification and Estimation of Stem Volume and Dbh Based on Single Tree Extraction by Exploiting

Airborne Full-Waveform Lidar Data." *Remote Sensing of Environment* 123:368-380. doi: 10.1016/j.rse.2012.03.027.

Yu, Q., P. Gong, N. Clinton, G. Biging, M. Kelly, and D. Schirokauer. 2006. "Object-Based Detailed Vegetation Classification with Airborne High Spatial Resolution Remote Sensing Imagery." *Photogrammetric Engineering & Remote Sensing* 72 (Generic):799-811. doi: 10.14358/PERS.72.7.799.

Yuan, F. 2008. "Land-Cover Change and Environmental Impact Analysis in the Greater Mankato Area of Minnesota Using Remote Sensing and Gis Modelling." *International Journal of Remote Sensing* 29 (4):1169-1184. doi: 10.1080/01431160701294703.

Yuan, F., J.J. Lopez, S. Arnold, A. Brand, J. Klein, M. Schmidt, E. Moseman, and M. Michels-Boyce. 2017. "Forestation in Puerto Rico, 1970s to Present." *Journal of Geography and Geology* 9 (3):30. doi: 10.5539/jgg.v9n3p30.

Yuan, M., M. Dickens-Micozzi, and M.A. Magsig. 2002. "Analysis of Tornado Damage Tracks from the 3 May Tornado Outbreak Using Multispectral Satellite Imagery." *Weather and Forecasting* 17 (3):382-398. doi: 10.1175/1520-0434(2002)017<0382:AOTDTF>2.0.CO;2.

Zhang, C., and F. Qiu. 2011. "Mapping Individual Tree Species in an Urban Forest Using Airborne Lidar Data and Hyperspectral Imagery." *Photogrammetric Engineering & Remote Sensing* 78 (10):1079-1087.

Zhang, C., Y. Zhou, and F. Qiu. 2015. "Individual Tree Segmentation from Lidar Point Clouds for Urban Forest Inventory." *Remote Sensing* 7 (6):7892-7913. doi: 10.3390/rs70607892.

Zhao, X., Q. Guo, Y. Su, and B. Xue. 2016. "Improved Progressive Tin Densification Filtering Algorithm for Airborne Lidar Data in Forested Areas." *ISPRS Journal of Photogrammetry and Remote Sensing* 117:79-91. doi: https://doi.org/10.1016/j.isprsjprs.2016.03.016.

Zhen, Z., L. Quackenbush, and L. Zhang. 2016. "Trends in Automatic Individual Tree Crown Detection and Delineation—Evolution of Lidar Data." *Remote Sensing* 8 (4):333. doi: 10.3390/rs8040333.

Zhou, W., and A. Troy. 2008. "An Object-Oriented Approach for Analysing and Characterizing Urban Landscape at the Parcel Level." *International Journal of Remote Sensing* 29 (11):3119-3135. doi: 10.1080/01431160701469065.